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COPING WITH UNCERTAINTY IN WATER QUALITY MANAGEMENT THROUGH CHOICES OF POLICY INSTRUMENTS AND INFORMATION INVESTMENTS

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Abstract

Traditionally, information collection for water quality management has been focused on biological data to describe environmental conditions, and stressor-condition-response relationships. While this kind of information is essential, other types of information – e.g., economic information about the benefits and costs of alternative policy actions – may be equally important for efficient management.

In this dissertation, I examine the performance of alternative strategies for managing ecological risks related to nutrient pollution in the Susquehanna River Basin (SRB) under alternative economic and ecological information structures. The SRB is the major source of nutrient pollution and related ecological damages in the Chesapeake Bay. The water quality management strategies are differentiated by nutrient reduction targets for subwatersheds of the SRB, and the environmental instruments used to pursue these goals. I define performance as the expected net benefits (pollution control benefits less costs) achieved by the strategies. The analysis allows me to estimate how the reduction of economic and ecological uncertainty can influence the optimal design of the strategies, and also estimate the value of different types of information in improving the performance of the strategies.

The study is based on a coupled numerical economic-biophysical model. Uncertainty is modeled by randomizing the values of model parameters using Monte Carlo simulation techniques. The results show that the value of all types of information is strongly dependent on the policy instruments used in water quality management. I also find that information about the economic benefits of pollution reductions has the highest value regardless of the management strategies. The value of information and policy

performance results are sensitive to the assumptions about the functional forms and initial amount of information available to water quality managers. However, the *relative performance* of alternative policy instruments and *relative ranking* of information collection strategies are independent from the assumptions.

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Abbreviations

CWA - clean water act

ESS – expected social surplus

NB – net benefits

NPS – nonpoint sources

SRB – Susquehanna River Basin

SS – social surplus

PS – point sources

VOI – value of information

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Chapter 1. Introduction

Every day the world around us brings surprises. They can be nice, as in winning a lottery, or not very pleasant, as in a farmer losing a crop to hail, or finding that a newly purchased car is a “lemon.” However, the fact that we don’t have perfect foresight about the weather, the mechanical status of our cars, or other events that may influence our circumstances does not exempt us from making decisions with uncertain outcomes. To make better decisions, we seek information from weather forecasts, auto mechanics, and other sources to reduce our uncertainty.

The necessity of making decisions with imperfect information is a feature not only of our individual daily lives, but also of collective decision-making about public goods. And public decision makers, like individuals, must balance the benefits of additional information for decision making against the costs. For example, the possible effects of climate change on ecological and economic components of societal welfare are extremely uncertain. Our projections of the changes in local climates, terrestrial and aquatic ecosystems, freshwater and food supply, extreme weather events and sea level rise are inaccurate due to the lack of reliable data and imperfect understanding of the global environmental processes. In addition, the costs of the greenhouse gas emission control are not perfectly known by the regulator. The costs depend on private decisions of polluters and are only privately known [Nordhause and Pope 1997]. Collecting better information about the timing, scope, impacts, damages, and potential costs of abating would assist the policy decisions by giving better understanding of costs and benefits associated with alternative policy actions. However, information gathering is an expensive and time-consuming task. Accordingly, the priority directions for data gathering and research should be selected based on comparison of the costs of data collection with the payoffs in terms of improved economic performance of regulation.

Another important contemporary example is decision making for water quality protection. Water pollution causes significant societal losses due to damaged fish and wildlife resources, human health hazards, and losses of recreational opportunities. However, imperfect information about costs and benefits can complicate policy decisions to protect and restore water resources. This has become very apparent to water quality managers in the U.S. in recent years, as they have struggled to comply with the U.S. Environmental Protection Agency's (EPA's) Total Maximum Daily Load (TMDL) regulations. The 1972 Clean Water Act established water quality goals ("fishable and swimmable" conditions in all navigable waters) and a regulatory framework for achieving them (technology based discharge standards for point sources). The regulations are credited with reducing discharges from point sources and improving water quality. However, significant water quality problems remain in many regions of the nation, often because measures were not taken to reduce pollution loads from nonpoint sources (NPS), such as agriculture, urban developments and atmospheric deposition. The major initiative to remedy the nation's water quality problems is the TMDL program. It was initiated in 1992 in response to law suits demanding that EPA enforce Section 303d of Clean Water Act, which requires additional pollution control measures when existing technologically-based regulations do not achieve water quality targets. EPA's TMDL regulations require states to list waters that are not meeting water quality criteria. For each listed water body, the states must identify the amount by which pollution loads from different sources must be reduced to meet the standards, and to develop and implement plans to achieve the load reductions [NRC 2000]. The states were to accomplish this task in 8 to 13 years. In July 2001, the U.S. EPA announced a delayed in the implementation of the Total Maximum Daily Load final rulemaking for 18 months [NRC 2000, Pfleger 2001] because of the enormous problems states were encountering in meeting the mandate. The slow progress has been attributed in large degree to the fact that key information for assessing the condition of streams, lakes, and estuaries, developing sensible plans to restore impaired waters was unavailable and costly to obtain [NRC 2000].

In this research, I examine the problem of controlling water pollution loads from agricultural nonpoint sources as an environmental policy design problem in which the objective is to select a nonpoint source pollution control instrument (e.g., tradable permits or taxes for nitrogen fertilizer application) that is expected to bring the highest benefits to the society. The choice must be made with imperfect information about economic and biophysical relationships. The expected improvement in policy performance due to information collection (the value of information) is compared for alternative information types and policy designs.

1.1 Agricultural nonpoint source regulation

The basis of water quality regulation in US is the Clean Water Act (CWA), which was passed in 1972. Section 402 of the CWA establishes the National Pollutant Discharge Elimination System (NPDES) to control point sources of pollution (PS). Under the system, PS are required to have permits in order to discharge pollutants into surface waters. The discharge limits are based on technological or water quality standards. Although NPDES has achieved significant reductions in pollution discharges, water quality goals have not been met in many cases because nonpoint pollution load has not been reduced [Ribaudo 2001, US EPA 2003a, Folmer *et. al.* 1995, US EPA 2003b].

The CWA established no comparable regulations for agriculture and other nonpoint sources (NPS). Instead, the Act shifted responsibility for NPS to the states. The states largely choose voluntary compliance approaches (such as education, research and development, and green payments), which have had limited impact on nonpoint pollution load. The focus on voluntary approach is due in part to the difficulties involved with designing and administering environmental policies for agriculture, which are often cause by deficiencies in reliable data about the environmental impacts of individual NPS [Ribaudo *et. al.* 1999]. It is also due to the political influence of agricultural producers, who prefer voluntary measures to enforceable instruments that induce changes in production and pollution practices and usually increase costs of production [Horan *et. al.* 2001].

Furthermore, the costs of achieving water quality improvements could have been substantially smaller [Freeman 1982]. Since the NPDES emphasizes uniform technology based effluent standards, little flexibility was allowed for achieving pollution reductions at least cost either through allocation among alternative PS, or between PS and NPS [Folmer *et. al.* 1995].

Remaining water quality problems attract a lot of interest of general public, policy-makers and scientists to the question of developing sound environmental policies that would target both NPS and reduce water pollution cost-effectively. However, NPS regulation is a challenging task. It requires implementing new approaches that take into consideration unique characteristics of nonpoint pollution, such as: a) impossibility to monitor individual runoff due to diffuse nature of pollution; b) weather-related variability; c) variation over geographic scope; c) difficulties in measuring economic damages caused by pollution [Ribaudo *et. al.* 1999].

Policymakers have a menu of policy tools available for addressing NPS pollution, such as economic incentives, standards, and liability rules. Which ones are most appropriate depends on a number of economic considerations, including how well the instrument achieves the policy goals, the costs of pollution control, monitoring and enforcement costs, and the ability of regulation to adjust to different economic and physical conditions [Ribaudo *et. al.* 1999].

1.2. Design of NPS pollution regulation

Adopting the framework suggested by [Shortle and Horan 2001], developing NPS regulation involves the choices of a) criteria for evaluating environmental and economic performance (e.g., the difference between economic benefits and costs of regulation); b) a subset of polluters who are responsible for environmental degradation and who can be easily monitored and controlled (whom to target?); c) the indicators to judge polluters' environmental performances (what to target?); d) policy instrument to induce polluters to improve their environmental performance (which instrument to use?). Each of the choices depends on the information available to water quality managers, and in turn, determines the information requirements for policy design.

1.2.1. Decision criteria

A decision criterion is required to rank the policies based on their outcomes. There are a number of criteria that can be used to judge environmental policies based on environmental and/or economic considerations. I focus on economic criteria.

Two commonly used economic criteria to judge the policy decisions are 1) the maximization of net benefits and 2) the least-cost achievement of environmental objectives. The former criterion implies choosing the regulation that maximizes the difference between the economic benefits of economic activity and the costs of resulting environmental damages. In the case of uncertainty, the concept is generalized to compare *expected* benefits and costs [Baumol and Oates 1988, Shortle 1986]. Alternatively, the environmental objectives can be selected based on non-economic criteria. In this case, alternative policy decisions evaluated with respect to their cost-effectiveness [Baumol and Oates 1988]. The environmental objective can be chosen by agreement among all the affected parties, or by ecological considerations, such as protection of endangered species with no known economic value. Applying the second criteria reduces the policy information requirements by eliminating the need in the data about the economic costs of environmental degradation.

1.2.2. Whom to regulate?

The decision about whom to regulate involves two choices: 1) the selection of a subset of suspected polluters to regulate (spatial scope); and 2) the decision about how similar or different the selected polluters will be addressed (spatial differentiation).

Consider the first choice. The diffuse nature of the NPS pollution makes it expensive to monitor individual emissions and creates the uncertainty about individual loadings. Expanding the set of the polluters under regulation results in the increase in the costs of pollution monitoring and policy enforcement [Shortle and Horan 2000]. On the other hands, targeting a small set of polluters implies higher burden on each of them in order to achieve pollution reduction objective, than in the case when all polluters are regulated. This burden can be reduced by re-distribution of pollution reductions if more polluters are controlled, thus reducing the costs of regulation [Shortle and Abler 1995, Shortle and Horan 2000]. In other words, there is a trade-off between the costs of achieving environmental objective, and the costs of monitoring (i.e. information collection) and policy enforcement.

Now, consider the choice of policy spatial differentiation. The characteristics of NPS pollution vary by location due to the great variety of farming practices, land forms, climate, and hydrologic characteristics found across even relatively small area [Ribaudo *et. al.* 1999]. Economically optimal regulation would be unique for each polluter depending on her pollution abatement costs and environmental impacts [Ribaudo *et. al.*1999]. However, such policy requires polluter-specific information, which is usually costly to collect. To reduce the costs of data gathering, the same (uniform) regulation can be imposed to all polluters. That is, the decision about the degree of policy differentiation among polluters involves balancing of policy economic efficiency and the costs of information collection.

Limited studies have addressed the issues of polluters' targeting and policy differentiation. These studies will be reviews in the subsequent chapters.

1.2.3. What to target?

Economically and ecologically justified candidates for the measuring and regulating polluters' environmental impacts will be 1) correlated with environmental conditions, 2) enforceable, and 3) targetable in time and space [Braden and Segerson 1993, Shortle and Horan 2001]. Emission is one of the most commonly discussed bases for regulation, especially in the context of PS control, due to its high correlation with environmental impacts of individual polluters. However, in the case of NPS pollutions, emissions of individual producers are prohibitively costly to monitor and control. That is this indicator is not easily targetable and enforceable [Shortle and Horan 2001].

Alternatively, environmental policy could be based on monitoring of ambient water quality, which well characterizes the overall environmental impacts of economic activities in a watershed. However, NPS pollution enters water systems over a broad front and is affected by stochastic natural processes (such as weather), which prevents identification of individual pollution sources. That is, the indicator is often poorly correlated with environmental impacts of individual polluters and do not send a clear signal to polluters of how to improve their environmental performance [Ribaudo *et. al.* 1999].

Another option, which is often discussed in the context of NPS control, is the regulation of inputs, which directly influence pollution runoff (e.g., fertilizer use)

[Shortle and Horan 2001]. Using production inputs as an indicator of polluters' environmental performance can significantly reduce the costs of pollution monitoring, given that the input use is observable. Unfortunately, only some production inputs are purchased on the markets and can be easily monitored (e.g., fertilizer of land purchases). Others (such as timing and location of fertilizer application) can be very costly to monitor, target and enforce.

1.2.4. Which instrument to use?

Economic theory describes a variety of policy instruments that can be used to induce the pollution reductions (e.g., standards, taxes, or tradable permits) [Shortle and Horan 2001]. The instruments can be divided into economic incentives and command-and-control mechanisms [Ribaudo *et. al.*1999]. Economic incentive-based instruments, such as taxes or subsidies, are used by policy makers to create prices for negative environmental impacts (i.e., economic damages), so that producers have incentives to control pollution at socially desirable levels [Ribaudo *et. al.* 1999]. Command-and-control approach sets standards for producers' behavior (e.g., prescribes a technology or specified level of fertilizer use) [Ribaudo *et. al.* 1999].

Under perfect information, different policy instruments often can be designed to achieve the same expected net benefits [Shortle and Horan 2001]. Accordingly, the instruments will have the same ranking given the economic efficiency criterion. To the contrast, with uncertainty, the mechanisms often produce different economic and ecological outcomes [Weitzman 1974, Baumole and Oates 1988]. Although the ranking of policy instruments under uncertainty has been the focus of the economic studies for 30 years, a little guidance is provided for selecting the policy instruments in an *empirical* situation. Most research is based theoretical models with a set of restrictive assumptions that often are not satisfied in the real world [see, for example, Weitzman 1974 and Malcomson 1978].

This research empirically examines (1) how the choice and design of instruments for water quality protection is influenced by the information available to decision-makers, and (2) the value of different types of information for water quality management.

1.2.5 Value of information

Given uncertainties, water quality managers can either choose a policy which minimizes information requirements, or invest into data collection. Information collection improves decision makers' expectations about the true values of benefits and costs of a policy alternative, thus decreasing the losses in policy efficiency due to deviation of expected and realized policy outcomes. But then, with limited resources for learning, where should information investments be focused? The priorities for data gathering can be determined by comparing the expected improvement in policy performance due to data collection and the costs of data gathering. Obviously, the information that is expected to significantly improve the policy performance, and that does not require much time and efforts to be collected, should be gathered first.

In the same way as the design of a policy is shaped by the amount and type of information available to the decision maker, the value of information depends on the policy design. For example, the value of the damage cost information is smaller in the least-cost framework than for the net benefit maximization criterion, since such information is not used to judging environmental performance in the least-cost framework. Another example is the dependence of the value of information about private pollution control costs on the policy instrument used. The value of this information is smaller for the pollution trading mechanisms than for the command-and-control approach, since the former mechanism reveals the private abatement costs information in the process of trading.

1.3. Objectives of current research

The foci of this research are the closely interrelated issues of the choice among alternative environmental policy instruments with imperfect environmental and economic information, and the value of different types of information for decision-making.

More specifically, the following issues are investigated:

a. The performance (measured by economic net benefits) and ranking of price and quantity nitrogen pollution controls under alternative information structures;

b. The value of different types of information for alternative policy instruments (measured as improvement in policy performance due to data gathering)

c. The effects of the policy spatial differentiation (i.e. uniform versus differentiated instruments) on information value and policy instrument ranking

d. The impact of policy spatial targeting (i.e., number of watersheds regulated in the region) on policy expected net benefits and information value;

e. The influence of the prior knowledge of decision makers on the policy ranking and information value;

f. The effect of the assumptions about functional relationships in the system on the policy ranking and information values.

1.4. Study Region

The empirical analysis is conducted using a model that simulates pollution control costs, pollution transport, and pollution damage costs in 8 subwatersheds of the Susquehanna River Basin (SRB). The SRB covers about half of the Pennsylvania, and it comprises 43 percent of the Chesapeake Bay's drainage area. The Susquehanna River is the largest tributary of the Chesapeake Bay, providing 90 percent of the fresh water flows to the upper half of the Bay and 50 percent overall [SRB Commission 1998]. Out of 73% of the stream Susquehanna miles assessed, 11% are considered to be impaired [SRB Commission 2003]. Nutrients (nitrogen and phosphorus) are main pollutants in the Susquehanna, along with the sediments and toxics. Nutrients introduced into the Susquehanna are transported downstream and make up 20 percent of phosphorus and 40 percent of the nitrogen found in the Chesapeake Bay [Alliance for the Chesapeake Bay 2003]. Nutrient loading is a leading cause of environmental degradation in the SRB and Chesapeake Bay, primarily because it results in accelerated algae growth. When algae decompose, they consume oxygen, depleting the water's oxygen supply, a crucial element for survival of the water organisms, such as Chesapeake's shellfish and fish stocks [Natural Resources Defense Council 1998].

In 1987, the District of Columbia; the States of Maryland, Virginia, and Pennsylvania; and the Federal Government signed an agreement to reduce the amount of nitrogen and phosphorus entering the Bay by 40 percent by 2000. Various pollution-reduction strategies were put into place by the States, including statewide control of runoff from urban areas, farmland, and pastures; improvements in sewage treatment; and preservation of forest and wetlands, which act as buffers to nutrient-pollution inputs. The objective was not achieved in time, partially due to the lack of funding, imperfect knowledge about economic activities and environmental processes causing/leading to pollution, and the reluctance to impose strict regulation that can intervene with economic objective. In 2003, the parties agreed to achieve this objective by 2010. This would require developing efficient pollution reductions strategies and regulations, which makes the topic of the current paper especially important.

1.5. Model description

This research focuses on regulation the nitrogen water pollution from corn production. Agriculture is the leading source of nutrients, accounting for 50% of the nitrogen found in the Susquehanna [PA DOP 2000]. Among different agricultural crops, corn production accounts for 30% of total nitrogen loadings delivered to surface water in the SRB [SRB Commission 1998]. This percentage rises even higher (approximately 67%) if atmospheric deposition is excluded [Abler *et. al.* 2002][1].

The empirical analysis is based on the coupled economic-biophysical model that simulates the effects of water pollution control instruments on polluters' resource allocation decisions, the costs the polluters incur from changes in resource allocation, and the effects of their choices on pollution loads and environmental conditions in the SRB and the Chesapeake Bay (see Fig. A1 in Appendix A). Economic benefits from corn production are defined as a sum of producers' quasi-rents and economic crop land rents. Corn production is modeled as a function of land, nitrogen use, with all other inputs aggregated into a single composite input. Nitrogen and land use are modeled explicitly, since their use directly affects amount of nitrogen runoff from a field. The pollution transport component simulates hydrological processes that drive transport of pollutants to the mouth of each sub-watershed and further to the Chesapeake Bay. Finally, the economic damage costs component aggregates three processes that determine economic losses due to environmental pollution in the Chesapeake Bay region: biophysical responses to pollution, resulting changes in services provided by water system, and economic evaluation of these changes [Ribaudo *et. al.*1999]. These processes are simulated with a single environmental damage cost function.

To model decision makers' uncertainty, alternative functional specifications of producers' profits and damage costs are analyzed. In addition, in each of the functional forms considered, some parameter values are assumed to be random.

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[1] Nonpoint sources are the leading cause of pollution in SRB and Chesapeake Bay [Chesapeake Bay Program 1999], and pollution from corn production is roughly 81% of all nonpoint nutrient loads [Carmichael and Evans 2000].

The model is developed based on readily available literature sources. That is, I reproduce the cheap (minimal) information on hand of the policy makers. The policy design is analyzed for five information scenarios, in which *ex ante* (minimal) information is available, or perfect information about pollution control costs, pollution transport, damage costs or all of the imperfectly known parameters is expected to be collected. The expected improvement in policy performance due to data gathering is used to estimate the value of information.

Performance of alternative policy spatial targeting (the number of watersheds regulated) and policy differentiation (uniform versus differentiated policies) schemes are compared. Their effect on the value of information is examined.

1.6. Overview of the presentation

In the next chapters, I first, present an overview of uncertainties in the water quality protection and their implications for policy design. Value of information theory is then examined in relation to environmental policy design. The research methods are presented in chapter three. Then, the model calibration and data source are discussed. Next, I describe the simulations conducted and results of the simulations (chapter five). The last chapter presents conclusions and perspectives for future research.

Chapter 2. Environmental policy design under uncertainty

Addressing water pollution problem in a way that is not unduly burdensome to society requires consideration of how pollution control policy initiatives will affect economic choices that determine pollution loads (such as discharges or agricultural production practices), as well as balancing the costs of the changes in resource allocation and the decrease in environmental damages. Moreover, public support for pollution control initiatives is unlikely when the benefits do not justify the costs. Consequently, economic information on both abatement costs and environmental benefits is essential for sound environmental policy design. However, many of the economic and biophysical variables relevant to policy design are not known by decision-makers.

Below, I first present an overview of the types of uncertainties in watershed management, and the effects of the uncertainties on the environmental policy design and economic efficiency. Then the literature on the effects of information collection on economic efficiency of a policy is examined.

2.1. Types of uncertainty

It is useful to group the sources of uncertainty in watershed management into two broad categories: (i) imperfect information about relevant *economic* characteristics (e.g., costs of pollution control, benefits of water quality improvements), and (ii) imperfect information about relevant *biophysical* conditions and relationships (e.g., the existing status of water resources and aquatic life; the relationship between pollution load and biochemical parameters of water quality).

2.1.1. Imperfect information about relevant economic characteristics

A classic problem in the theory of regulation is that of asymmetric information. This problem arises when information, which a regulator needs to design societally optimal policies, is only private knowledge. In environmental regulation, asymmetric information problem can arise from private knowledge about the costs and benefits of pollution controls (adverse selection), or about private actions affecting societal risks (moral hazard).

First, let me consider the *moral hazard* problem. Diffuse nature of NPS pollution makes monitoring of the pollution runoff from a field and loadings into water systems an expensive and challenging task [Ribaudo *et. al.* 1999]. The inability to observe loading would be mitigated if there were a strong correlation between ambient quality of a water body and some observable aspect of production (e.g., a production input) [Ribaudo *et. al.* 1999]. However, such correlations are very rare due to the interference with the other natural/human-induced factors (such as weather events). As a result, a policymaker is uncertain as to whether poor water quality is due to producers' failure to take appropriate actions, or to undesirable states of nature, like excessive rainfall [Ribaudo *et. al.* 1999]. In turn, some of the production inputs which are critical for forecasting NPS pollution can be unobservable or prohibitively expansive to monitor [Ribaudo *et. al.* 1999]. Since regulators can not monitor environmental performance, producers have incentives to decrease pollution abatement costs by reduction in abatements [Hanley *et. al.* 1997].

Several authors have addressed the moral hazard issue (e.g., Dosi and Moretto [1993, 1994]). A classic paper is by Segerson [1988]. In her research, the regulator seeks to maximize expected social surplus in a hypothetical region with many heterogeneous firms. Emissions are deterministic functions of inputs, but environmental damages are stochastic function of firms' emissions. The profit and environmental damage costs functions, as well as the distributions of random parameters, are common knowledge of regulator and producers. However, the regulator cannot monitor producer's input use. Segerson proves that optimal pollution reductions and input uses can be achieved when each polluter pays the full marginal damage costs, rather than just the firm's share of damages. Cabe and Herriges [1992], Xepapadeas [1994] and others further developed the mechanism suggested by Segerson. However, the following information-related factors can hinder the practical application of the ambient-based policy mechanisms: possibly high cost of monitoring and considerable monitoring error, the link of current ambient conditions to the activities far in the past, and the considerable information burden for polluters, who need to understand the effects of their actions on ambient conditions [Shortle and Horan 2001].

Another type of asymmetric information - *adverse selection* - arises when an individual's decisions depend on her privately held information in a manner that adversely affects uninformed participants [Mas-Colell *et. al.* 1995]. For regulatory authorities, it is expensive to monitor polluters' compliance costs. As a result, compliance costs are often only privately known, and the authorities are unable to design a policy that minimizes total costs of environmental goal achievement.

Several studies have been focused on policy implications of the adverse selection problem (e.g., Weitzman 1974, Dosi and Moretto 1994). A classic paper is by Shortle and Dunn [1986]. They consider the situation when regulators' objective is to maximize social surplus in a hypothetical region. The regulators do not know the firm's profit levels and hence, abatement costs. The emission function is uncertain because of stochastic weather parameters. However, the regulators can observe and control producers' input choices. The authors show that input tax scheme can be used to bring about *ex ante* efficient policies.

Apart from asymmetric information, some economic parameters are not known to both polluters and regulators, such as future input and output prices, the values of future use of resources (option values), technologies that will become available, etc [see, for example, Sunding and Zilberman 2000]. Environmental instruments can be designed based on the polluters' and environmental authority's expectations about the imperfectly known parameters.

2.1.2. Imperfect information about biophysical characteristics

Another general source of uncertainty – imperfect information on natural conditions and processes - can be divided into epistemic and aleatory uncertainties [NRC 2000, Hession 1996]. Aleatory uncertainty refers to unexplained random variability of some environmental characteristics, such as the weather or river flow [NRC 2000, Bobba *et. al*. 2000]. Such uncertainty is inherent characteristic of natural systems and can not be reduced by collecting additional information. Epistemic uncertainty refers to incomplete understanding or inadequate measurement of critical biophysical conditions, stressors and other natural system properties. This uncertainty is a property of decision makers (subjective uncertainty), and can be reduced by additional observations of the system [Kao and Hong 1996].

As for the case of imperfect information about economic parameters, environmental policy can be based on the expectations about the biophysical parameters and relationships. Among the other studies analyzing the effect of biophysical uncertainties on policy design are the important works by Weitzman [1974], Stavins [1996] (a description of these studies is presented in subsequent sections).

In this research I will examine how economic and biophysical uncertainties influence the design and economic efficiency of instruments for water quality protection, and the value of investments to improve information for environmental policy design.

2.1.3. Characterization of uncertainty

Imperfect knowledge about biophysical and economic system characteristics can take the form of model or parameter uncertainties [Bobba *et. al.* 2000, Finkel and Evans 1987]. Imperfect knowledge of functional relationships (model uncertainty) is an ambiguity about the variables affecting the process of interest, and the functional relationships among these variables. Parameter uncertainty is the inability to predict the parameter value with sufficient confidence, due to measurement error, sampling variability, or lack of observations, the numerical values of the key variables [Bobba *et. al.* 2000, Finkel and Evans 1987].

To provide context, below I discuss some dimensions of environmental decision-making and role of various types of information in addressing them.

2.2. Policy design under uncertainty

Adopting the framework suggested by Shortle and Horan [2001] and Horan and Shortle [2001], environmental policy design involves the choices of a) criterion to judge performance of policy alternatives; b) the indicators of polluters' compliance and water quality goals, c) the subset of polluters to target; d) the degree of policy differentiation among polluters; and e) the policy instrument used to induce changes in polluters' production practices.

2.2.1. Decision criterion

Three general characteristics that are usually used to evaluate environmental policy are effectiveness, efficiency, and equity [Zilicz 1995]. The policy is said to be *effective* if it solves the problem it was supposed to. The effectiveness is the most important policy aspect for the environmental activists who concentrate on such environmental outcomes as clean water, protected biodiversity, etc [Zilicz 1995].

However, effectiveness does not characterize the costs of achieving environmental goals. Hence, economists prefer the concept of *efficiency*, which implies accounting for both the costs and effects of a policy [Zilicz 1995]. The environmental effects are made comparable with abatement costs by evaluating the former and the later in the same terms, usually, in terms of money.

As in the case of effectiveness, the idea of efficiency leaves aside the question of fairness, that is who will pay the costs and who will benefit from the effects. *Equity* characterizes the distribution of costs and benefits among the parties of concern [Zilicz 1995].

Economics focuses on the policy efficiency. An efficient solution is one that maximizes social surplus – the private net benefits of production minus the expected economic costs of pollution [Ribaudo *et. al.* 1999]. An efficient policy leads to such allocation of pollution reductions that for each site the marginal net private benefits and marginal environmental damages are equal [Ribaudo *et. al.* 1999].

Although the maximization of social surplus results in societally optimal allocation of pollution reductions, such approach is very information intense. It requires the knowledge of the relationships between pollution loading, ambient concentration, the state of water ecosystems, and services provided by a water body. That is, it requires measuring environmental damages in monetary terms. Such information is usually difficult to obtain [see, for example, Boyd 1998, Navrud and Pruckner 1997]. To decrease policy information requirements, a somewhat less stringent concept of *cost-effectiveness* can also be used to analyze the policy performance. A cost-effective policy achieves required environmental effect at the least possible costs [Zilicz 1995]. An example of such framework is achieving water quality standards with minimal costs. However, with such framework, there is no guarantee that the environmental objective is selected optimally [Zilicz 1995]. For example, pollution reduction objective can be too costly to achieve when compared with the benefits that a community receives from an unpolluted water body.

2.2.2. Water quality goals, indicators, and compliance measures

As noted above, the information required for environmental policy decision-making depends on how the environmental problem is formulated. Designing an environmental policy involves a choice of a water quality target and a set of means for achieving the target. For instance, if we can describe the physical, chemical, and biological components of water quality by a vector Q, then the environmental goal entails a choice of a target level for Q. The means for attaining the goal are the policy instruments that are used to induce changes in stressor levels through changes in the behavior of economic agents. Instruments can be differentiated according to the variables that are measured for assessing the regulatory compliance of individual economic agents (e.g., the use of agricultural Best Management Practices or discharges from a sewage treatment plant), and the type of mechanism used to induce change in polluters' behavior (e.g., standards or charges). I will refer to a variable that is measured for assessing the regulatory compliance as a basis. The societal and environmental consequences of a policy will depend on both the choice of ends and means.

The choice of environmental goals is an information intense task. Environmental goals can be defined at various levels. In the case of TMDLs, an upper level goal is the designated use of the water resource. A reasonable choice requires the consideration of what is feasible, of costs and benefits, and is based on available information [NRC 2000]**.** The operational goal(s) or standards that specify the levels of environmental indicator(s) and are monitored to measure attainment of water resource conditions necessary for the designated use (e.g., measures and standards for the specific physical, chemical, and biological attributes that must be met to support a cold watery fishery) are ascribed to the next level. Significant informational issues must be addressed when choosing such indicators and goals for them. Environmental indicators have been categorized as pressure and response indicators [European Environmental Agency 2003]. The former describe pollution loads, land uses, or other variables that are stressors on environmental systems. The latter describe the physical, chemical, and biological conditions of resources, and possibly human responses to changes in environmental conditions.

Ideally, indicators used in the definition of operational goals will be response indicators that are valid and reliable for measuring whether the resource supports the designated use, and measured at reasonable cost. Unfortunately, as the TMDL experience has shown, such indicators are not always available [NRC 2000]. Costs considerations or limitations of scientific knowledge force managers to use environmental indicators and corresponding operational goals that are limited in their validity and reliability. These "second-best" indicators and goals can be response indicators and related goals, pressure indicators and related goals, or a mix of both types.

A question related to overall goals and indicators for water resources is how to measure the environmental economic efficiency of individual pollution sources [NRC 2000]. Whether operational goals are attained generally will depend on the actions of individuals, businesses, and communities that determine the nature and level of point and nonpoint stressors. Effective management of these stressors will require measurement of the environmental efficiency of these economic agents. Ideally, the indicators used for monitoring the environmental economic efficiency and compliance of economic agents should be pressure indicators that are easily and directly connected with the actions that cause water quality impairment, and also capable of being routinely metered at reasonable cost. However, like the indicators for defining and measuring operational goals, there can be significant gaps between what is ideal and what is technically and economically practical.

The economics literature on environmental policy design usually recommends pollution discharges as the preferable target for measuring environmental performance provided that discharges can be metered routinely and at reasonable cost [Oates 1995;

Shortle and Horan 2001]. However, these conditions are not always satisfied. The case of nonpoint pollution sources of pollution is particularly noteworthy. The spatially diffuse nature and other characteristics of nonpoint source pollution loads make it prohibitively costly to determine the contribution of individual nonpoint sources to pollution loads [Shortle and Horan 2001, Ribaudo *et. al.* 1999]. Accordingly, monitoring the performance of nonpoint sources generally requires that decision makers choose alternative compliance measures. Options used in practice include discharges proxies (e.g. nitrogen application in excess of crops need) or pollution–related production and technology choices (e.g. fertilizer application, land use, conservation and tillage practices). The choice of compliance measure should be guided by information on the relationship between the compliance measure and the environmental conditions and monitoring costs. For nonpoint sources, input-based instruments are of particular interest because the monitoring the contributions of individual farms to nonpoint source loads is prohibitively costly [Shortle and Horan 2001; Ribaudo *et. al*. 1999].

2.2.3. Whom to regulate

In order to decide how to decrease pollution load into a water body, the polluting activities and specific pollution sources should be identified. Agriculture, industry, urban settlements, atmospheric deposition of air pollutants, and other sources contribute to water quality impairments; however, their relative contributions differ. Moreover, within each category of polluters – agricultural, industrial and urban - the contribution of each pollution source varies considerably. Complete detection and quantification of water pollution sources can be a challenging and information-demanding task, involving large spending on data collection, contacting polluters, monitoring and enforcement [Shortle and Horan 2001, Horan and Shortle 2001, Braden and Segerson 1993, Carpenier *et. al.* 1998]. Given high information costs, a complete accounting is uneconomic, and therefore an environmental agency targets a subset of polluters. Essentially, this is what has occurred in US water quality policies. Large obvious polluters have been the target of regulatory efforts, while smaller or less obvious polluters have been neglected.

However, the choice of a subset of polluters to regulate can result in the regulation of someone who causes little or no problem, and a failure to regulate someone who does contribute. In both cases, economic efficiency of the policy decreases [Shortle and Abler 1995]. For example, regulating just PS caused considerable inequality in abatement costs between PS and NPS [Malik *et. al.* 1994, Camacho 1991]. This disparity, as well as the overall policy abatement costs, could have been reduced if both categories of polluters (PS and NPS) were regulated, and pollution reductions were distributed among them. The information issue here entails balancing losses in policy social surplus due to targeting a subset of polluters against the information costs associated with regulating all polluters.

Several studies address the issue of regulating a subset of polluters. For example, Carpentier *et. al.* [1998] analyze nitrogen runoff standards for farms in the Low Susquehanna Watershed. They consider two alternative targeting schemes. The first option is to require all polluters in a watershed (237 farms) to reduce nitrogen runoff by 40%. Alternatively, a spatially targeted scheme can be used to set farm-specific reduction standards, focusing just on the farms with low compliance costs. The targeted scheme decreases the number of regulated farms from 237 to just 93, and as a result, the total costs of pollution control reduce to one-forth of the costs for the other regulation alternative. Schleich and White [1997] analyze cost-effective policies to reduce the total phosphorus and total suspended solids for Fox-Wolf river basin in Northeast Wisconsin. They show that high percentage of reductions can be achieved by regulating a few watersheds instead of the control for entire region.

To be effective, regulated subset should be small enough to make targeting worthwhile in terms of cost savings, and yet large enough to insure that the desired reduction in pollution for the watershed could be obtained [Bosch *et. al.* 1994]. This raises the issue of a basis for selecting a subset of polluters to regulate. For example, Carpentier *et. al.* [1998] suggest targeting polluters with low abatement costs. Alternatively, Schleich and White [1997] consider selecting polluters based on their estimated abatement costs *and* loadings. In Schleich and White [1997], if both PS and NPS are targeted, 99% reductions in total phosphorus and total suspended solids come from NPS. Hence, regulation can be designed exclusively for NPS without significant increase in costs of achieving overall environmental objective. At the same time, such targeted approach can reduce policy information requirements by eliminating the need in PS data.

2.2.4. Spatial differentiation and scope

By "spatial differentiation", I mean policy discrimination among alternative locations/polluters. One extreme is a policy designed uniformly for an entire country. An example is the national drinking water quality standards selected independently of the regional costs of compliance. Another example is the uniform technology-based effluent standards imposed on point sources under provision of CWA. The other extreme are the regulations that are unique to specific polluters in a small watershed.

For policy purposes, the polluters can be differentiated by types based on their abatement costs ("low" versus "high" costs) and pollution impacts ("low" versus "high" impacts). A policy is efficient if marginal abatement costs are equal marginal environmental damages for each polluter [Shortle and Horan 2001, Ribaudo *et. al.* 1999]. This efficiency requirement is satisfied for *differentiated policies*. Such policy prescribes significant changes in the input use for polluters of "low" abatement costs types and "high" environmental impacts. To the opposite, for polluters with "low" environmental impacts and "high" abatement costs, the required land and fertilizer use changes are insignificant.

The efficiency requirement is violated for *uniform* policies, which set the same level of regulation for the polluters with different abatement cost and environmental impact types. However, for a uniform policy, the information about site-specific factors is not required, and the information collection costs are reduced. Hence, decision makers face tradeoffs between the costs of collecting information for differentiated instruments and the losses in economic efficiency for a uniform regulation.

The disparity in the outcomes for the uniform and differentiated policies depends on how different or alike are the polluters in their abatement costs and environmental impacts. The policies perform the same if all the polluters are identical. In contrast, the benefits of the policy differentiation are greater when there is significant heterogeneity among polluters.

Several authors have compared the economic efficiency of spatially uniform and differentiated policies based on empirical models for particular regions. Their conclusions vary. Some research find that uniform policies are less information intense and hence, cheaper to control and enforce [see, for example, Fleming and Adams 1997; Moxey and White 1994; Helfand and House 1995; Hansen 2001]. Others find that targeting incentives to specific sites would significantly over-perform uniform approaches due to local geographic and hydrological conditions [see, for example, Babcock *et. al.* 1997, Russell 1986, Tsai and Shortle 1998, Johansson 2002; Schwabe 2001; Carpenier *et. al.* 1998]. The differences in their results are influenced by the degree of heterogeneity among polluters and the flexibility of farmers responses considered (e.g., if the substitution among inputs and/or agricultural activities is captured by the model used in the research). The more divergent the characteristics of polluters are and the more flexile the farmers in responses to the regulation, the more preferable are the differentiated policies. Kostald [1986] emphasizes the importance of the functional relationships assumed for economic and biophysical parameters in the research models. He studies performance of uniform and differentiated taxes and tradable permits on emissions in the Four Corner Region. The objective is to maximize social surplus from the regulation of air quality. The private profits and abatement costs are not observable by the regulators. The true functional form of the damage costs function is also unknown. The author finds that uniform emission control is reasonably efficient when damage function is linear or concave. For convex damage function, differentiated policies significantly outperform the uniform ones.

2.2.5. Which instrument to use

In the end, it is the policy instruments that induce changes in production and pollution control practices to achieve environmental policy objectives [Shortle and Horan 2001]. Instruments can be differentiated by the basis for measuring individual compliance and the type of mechanism used to induce changes in behavior [Shortle and Horan 2001]. The basis for regulation can be input use, production output, emissions or expected emissions, or ambient concentration (see the discussion about indicators and compliance measures above). By the type, policy mechanisms can be categorized as "command-and-control" and "incentive-based". Command-and-control instruments specify exact rules for polluters' activities (e.g. technological or discharge standards). In the contrast, incentive-based (or "economic") instruments leave polluters freedom to adjust their activities, but provide them with economic incentives to modify their choices in environmentally desirable ways. Economic instruments include price-rationing (e.g., charges and subsidies), quantity-rationing (e.g., tradable permits), and liability rules [Hanley *et. al*. 1997].

Economists have identified a menu of command-and-control and economic incentive instruments that can achieve economically optimal allocations of pollution control under perfect information [Shortle and Horan 2001]. For example, taxes on ambient pollution concentration can be used, or subsidies can be paid for implementation of best management practices. However, they have also found that instruments that perform equally well with perfect information are not equivalent under conditions of uncertainty about costs and benefits [Weitzmam 1974, Stavins 1996, Shortle and Horan 2001]. For example, command-and-control instruments are generally considered economically inferior to the incentive-based instruments because the command-and-control approach requires more information about pollution control costs than economic instruments to achieve equivalent results. For example, compare standards and tradable permits. For least-cost achievement of environmental goals, individual standards should be developed for each polluter based on his/her costs of abatement. In contrast, pollution trading requires setting just the aggregate emission quota for a region. Trading of pollution permits will achieve the least-cost allocation of pollution reductions among the producers without regulators' participation [Shortle and Horan 2001].

However, the economic efficiency of economic instruments also varies under the conditions of imperfect information.

2.2.6. Efficiency of economic policy instruments under uncertainty

In the case of uncertainty about the marginal costs or benefits of pollution control, Weitzman [1974] and others [Stavins 1996, Wu 2000, Shortle and Abler 1995] have shown that the relative ranking of optimized price and quantity instruments may differ depending on properties of the cost and benefit functions.

A classic paper about relative efficiency of economic instruments is Weitzman [1974]. In his very general approach, Weitzman assume that the random error characterizing uncertainty is sufficiently small to justify quadratic approximations of generalized total cost and total benefit functions or, in other words, linear approximations to the respective marginal benefit and marginal cost functions. He analyzes the uncertainties resulting in the shifts of marginal benefit and cost curves, and does not consider the imperfect knowledge about the slope of marginal curves. Based on these assumptions, he finds that the relative ranking of pollution abatement price and quantity instruments is given by [the formulation is after Stavins 1996]:

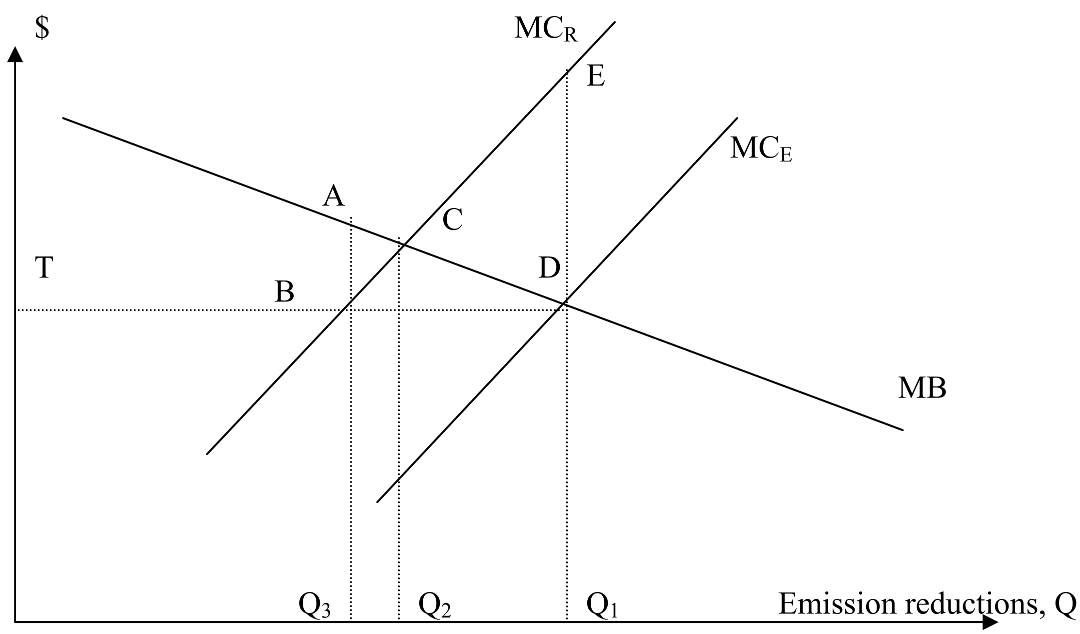
$$\Delta_{tq} \approx \frac{\sigma_C^2 \cdot B''}{2 \cdot C''^2} + \frac{\sigma_C^2}{2 \cdot C''} \tag{2.1}$$

where Δ_{tq} is the difference between expected social surplus of tax and quantity controls; B'' is the slope of the marginal benefit function, the second derivative of the total benefit function, B; C'' is the slope of the marginal cost function, the second derivative of the total cost function, C; and σ_C^2 is the variance of the abatement costs. That is, abatement cost uncertainty is a precondition for different efficiency of policy instruments. If abatement costs are known, the variance term σ_C^2 becomes zero, and the tax and quantity instruments result in the same expected social surplus.

The result is graphically presented on Figure 2.1. Suppose that the regulator knows the marginal benefits of control, but is uncertain about the marginal costs. MC_E and MC_R represent the expected and realized linear marginal abatement cost functions respectively, and MB represents linear marginal benefits of abatement. T is the tax set to achieve the expected socially optimal emission reduction; Q_1 is quantity control, say, quantity of tradable permits.

If marginal benefits MB are approximately constant across alternative levels of pollution control and the marginal benefits curve is almost flat, emission tax outperforms quantity control. Compare the losses associated with the mechanisms due to the deviation of expected and realized MC, which are represented by areas ABC and ECD on Figure 2.1. The realized marginal costs MC_R are assumed to be greater than anticipated (MC_E) for any control level, and the *ex post* efficient amount of emission reduction is Q_2. The social loss associated with the tax, the triangle ABC, is significantly less than that of the permit program, the triangle CDE. In the limit when MB are flat, tax control will achieve the societal optimum regardless of the realized costs if the tax rate is set equal to the marginal damages. Given this tax, the polluters will adjust the pollution levels in such a way that their privately known marginal abatement costs are equal to the taxes and hence to the marginal damage. And the further the realized costs deviate from the expectations, the worse the permits does [Hanley *et. al.* 1997].

Figure 2.1. Tax and Quantity Policy Instruments Ranking*



* adapted from Stavins [1996].

Alternatively, when the marginal benefits of control are extremely steep, tradable permits are preferable to the tax. Under the tax control, the polluters' adjustment of the abatement level according to the realized costs leads to an excessive/ insufficient pollution reductions when the costs are higher/ lower than predicted. And the further the realized costs deviate from the expectations, the worse the taxes perform. Alternatively, the fixed number of tradable permits will achieve nearly optimal level of pollution reductions regardless of whether realized marginal control costs exceed or are less than expected costs [Hanley *et. al.* 1997].

For the case with an "intermediate" slope of the marginal damages, both taxes and tradable permits will lead to some inefficiency. If costs are higher than expected, taxes lead to insufficient control, and permits lead to excessively strict regulation. If the costs are lower than expected, the situation is reversed. The relative policy ranking will ultimately depend on the slopes on the marginal costs and benefits curves and on the uncertainty about the marginal abatement costs [Hanley *et. al.* 1997].

Stavins [1996] expands the Weitzman's results above by showing that the covariance between marginal costs and benefits matters. He considered a situation with simultaneous and correlated benefit and cost uncertainty and showed that a positive correlation between damages and costs tends to favor the quantity instrument. Negative correlation always tends to favor the price instrument.

Weitzman [1974], Adar and Griffin [1976], Fishelson [1976], Roberts and Spence [1976], and Stavins [1996] focus on the emission-based instruments. However, NPS pollution is diffuse and the runoffs of individual polluters are costly to monitor and regulate. To decrease the monitoring costs, other bases for regulation can be used, such as producers' variable inputs [Ribaudo *et. al.* 1999]. Shortle [1984] and Shortle and Dunn [1986] compare the performance of input-based instruments. Their analysis is based on a model with asymmetric information about polluters' profits/abatement costs and stochastic weather events affecting polluting runoff. Regulators choose input standards, input taxes, expected runoff standards, or expected runoff taxes to maximize expected social surplus. The authors found that appropriately specified input taxes generally outperform input standards and expected runoff incentives and standards.

Wu [2000] and Wu and Babcock [2001] point out the effect of inputs substitution on the ranking of input-based instruments. The substitution effect increases the relative efficiency of standard if the regulated input has a close *substitute* that *reduces* marginal environmental damages. That is, the standard decreases the use of targeted input, and at the same time, increases the use of non-targeted low-polluting substitute, which further decreases the environmental damages. Economic efficiency of standards also improves if the input has a close *compliment* that *increases* marginal damages. That is, imposing standard decreases the use of pollution-increasing compliment and this reduction increases efficiency of the policy. However, if a regulated input has a compliment that reduces its marginal pollution costs, and the effect of marginal pollution costs is larger than the effect of marginal profits, the substitution effect favors taxes.

Instead of treating instruments as policy alternatives, a regulator can apply a mix of instruments, and improve policy efficiency. Roberts and Spence [1976] have constructed a hybrid policy that includes effluent tradable permits, fee and a subsidy. The system works as follows: the regulator issues a number of tradable emission permits. At the same time, the regulator allows polluters to generate emissions in excess to permits, but charges a fee per unit of such emissions. Finally, the regulator offers polluters subsidies per unit of any unused permit. If the three regulator-controlled parameters in the system (number of permits issued, emission charges and subsidies) are chosen to maximize expected social surplus, the result must be at least as desirable, as either only permit, or only emission tax schemes. Shortle and Abler [1995] developed a similar policy scheme, but based not on emissions, but on inputs of NPS.

While economists have demonstrated theoretically that information structures matter to the choice of instruments, the models they have used have been highly restrictive and therefore do not provide significant practical guidance about instrument choice in real world settings. For example, Weitzman [1974], Stavins [1996] and Wu [2000] base their analysis on quadratic approximation of the benefit and cost functions. They model uncertainties as imperfect information about the intercepts but not the slopes of the marginal benefit and cost functions. These are highly restrictive and unrealistic assumptions. Malcomson [1977] presents a generalized expression for the price and quantity policy ranking that does not require the benefits and costs to be quadratic. Given a certain characteristics of the distributions of the imperfectly known parameters, the decision maker can receive the opposite policy ranking depending on the application of the Malcomson's or the Weitzman's frameworks. Malcomson demonstrated that the nonlinearities in the abatement benefits and costs functions influence the relative ranking of the policies. However, the Malcomson's framework is too general to provide guidance in real-life situations. The more general the specification of the abatement benefit and costs functions are the more difficult to get an analytical solution about the policy economic efficiency and to interpret the results.

An empirical analysis that is performed for a specific region with particular abatement cost and benefit functions can provide more guidance to a policy maker. Unfortunately, many empirical studies that focus on relative economic efficiency of alternative policy instruments do not incorporate uncertainty [see literature review in Horan and Shortle 2001]. An example of the study accounting for uncertainty is Wu and Segerson [1995]. They compare policy instruments given biophysical uncertainty and the imperfect knowledge about future values of economic variables, but not the asymmetric information. The study focuses on ground water pollution in Wisconsin. The policy objective is to induce a 1% reduction in high-polluting corn acreage. The policy options considered are reductions in price for corn, increase in Acreage Reduction Program (ARP) for corn, and increase in chemical prices. ARP appears to be the most effective. However, the authors point out that the policies are analyzed based on their effects on the acreage decision. Such decision criterion does not account explicitly for environmental impacts of alternative instruments.

Many studies explore the impacts of policy from an *ex ante* point of view and do not analyze the value of information. For example, Braden and Segerson [1993] present an abatement cost curve for sediment pollution in a watershed in Central Illinois. The curve begins with a very little slope and becomes steeper as abatement cost is raised. They state that there is no corresponding information on the benefits (abatement demand). Given this, they can only speculate about the ranking of incentive and regulatory policies. If demand and supply intersect at low levels of abatement, then the demand curve would almost certainly be steeper than the very flat supply curve and an abatement standard set to achieve the expected pollution level would probably minimize the *ex post* losses in economic surplus. At the other extreme, the steep portion of the cost function would almost certainly be steeper than demand curve, in which case an incentive instrument would minimize *ex post* losses. However, different methods of estimating the cost function can produce different curvatures and different conclusions about the type of instrument that will minimize realized errors. Another study, Yulianti *et. al.* [1999], compares effectiveness (as measured in the costs to achieve environmental quality goal) of erosion taxes and standards in the Highland Silver Lake watershed (Illinois). They conclude that among different uncertain economic and biophysical factors, the rainfall erosivity has the greatest effect on policy economic efficiency. However, the authors do not analyze the expected increase in policy economic efficiency due to information collection (i.e., the value of information).

The policy elements discussed above - spatial resolution, allocation of load reductions, and the choice of mechanisms – are interdependent [see, for example, Nichols 1984 and Helfand and House 1995]. Policy economic efficiency and policy information requirements are determined by the combination of the elements. The objective of current research is to analyze the effects of spatial targeting and differentiation, and the choice of the regulatory instrument on the policy economic efficiency and information requirements. Both asymmetric information and imperfect knowledge about biophysical parameters are modeled and the effect of information collection on policy economic efficiency in terms of the value of information is considered.

2.3. Value of information

Given the pervasive uncertainties in water quality management, and impossibility to resolve them before making decisions, an adaptive approach to environmental policies implementation is essential [NRC 2000]. This implies a cyclical process in which policies are periodically assessed and revised. In the beginning of each cycle, environmental authorities have to decide how much data and of what type should be collected. Data collection improves policy economic efficiency but requires time and money spending

Value of information (VOI) concept allows estimation of the data collection effects on policy performance, which, in tern, helps to select priorities for data gathering. VOI is the expected gain in a money-metric measure of policy performance from utilizing additional information [Lawrence 1999]. In other words, VOI is the difference between expected *ex post* and *ex ante* social surplus. Once the benefits of improved knowledge are estimated, they can be compared with the data collection costs so as to reach an appropriate balance [Nordhaus and Popp 1997].

2.3.1. Formal presentation of VOI

Formally, the value of information can be described in the following way (the framework is adapted from Lawrence 1999). Denote the set of available and feasible policy alternatives by X. A policy decision is a choice of the specific action $x \in X$ (e.g., the level of input quota or tax) that satisfies a decision criterion. The decision criteria can be, for example, maximization of a payoff function F (e.g., maximization of the social surplus). The outcome of alternative actions x (i.e., $F(x, .)$) is affected by various un-controlled factors (e.g., the level of private abatement costs), and is not known precisely. Denote the un-controlled factors by a random vector Θ. It is assumed that the decision maker can identify possible realizations of the random events - possible "states of nature" - $\theta \in \Theta$ (e.g., high or low private abatement costs). The decision maker's beliefs about possible states on nature are reflected in the probabilities $p(\theta)$.

Given that payoff function F depends the realization of the random parameter θ, the decision maker has two alternatives. First, he/she can immediately choose an optimal action x_0 to maximize the expected payoff function:

$$\Pi_0 = \max_x \int_\theta F(x,\theta) \cdot p(\theta) \cdot d\theta \tag{2.2}$$

Alternatively, the decision maker can improve his/her knowledge about the random state variable by seeking additional information. Information is defined as any stimulus that influences the probability distribution assigned to states of nature θ. Suppose a decision maker receives an information message y (e.g., polluters' reports about their profits before and after pollution reductions). This message leads the decision maker to change probabilities of possible states. This change depends on the message itself and on the decision maker's confidence in that the message corresponds to the true state of nature θ (e.g., the decision-maker may not believe that the serf-reports of polluters convey accurate information about their profits). The decision maker's probability distribution over the possible state of nature after getting the message y can be denoted as conditional probability $p(\theta|y)$. Let x_y denote the optimal action posterior to the receipt of the message y:

$$\max_x \int_\theta F(x,\theta) \cdot p(\theta \mid y) \cdot d\theta \tag{2.3}$$

Assume information collection resolves all uncertainty, that is $y_i = \theta_i$ and $p(y) \equiv p(\theta)$. Then the decision maker's payoff posterior message $y_i = \theta_i$ is

$$\max_x F(x,\theta_i) \tag{2.4}$$

The decision about information collection should be made *before* information is obtained. That is, the possible results of information collection (all possible information messages $y \in Y$ and their probabilities $p(y)$) should be identified. For each possible outcome of data collection, *ex post* optimal policy action should be chosen. Then, expected policy performance given data collection can be estimated as the expectation of the *ex post* performance:

$$\Pi_1 = \int_{\theta} \left(\max_x F(x,\theta) \right) \cdot p(\theta) \cdot d\theta \qquad (2.5)$$

Then, VOI is the difference between expected payoffs with and without information:

$$\text{VOI} = \Pi_1 - \Pi_0 \qquad (2.6)$$

2.3.2. Determinants of VOI

The value of information depends on the following factors: a) the prior information available of the decision maker, b) the type of data collected (e.g., economic versus biophysical data), b) the accuracy and relevance of information to the decisions made, e) the decision options considered by decision maker, and f) the decision criteria used in the analysis [Lawrence 1999, Bosch *et. al.* 1994].

The information available to the decision maker *a priori* influences how valuable the additional data are for making a decision. The less information is available, the more "spread out" is the states' probability distribution $p(\theta)$. Information theory suggests several measures of uncertainty – variance, coefficient of variation, etc. The most universal and widely used measure is Shannon's entropy [Lawrence 1999]:

$$H = -\int_{\theta} p(\theta) \cdot \log\left(p(\theta)\right) \cdot d\theta \qquad (2.7)$$

The higher the entropy H, the less information about the system is available. The entropy is maximal for uniform distribution and is zero when there is no uncertainty about the realization of random variable (since log[1] = 0). Further, any change toward equalization of the probabilities increases entropy.

Intuition suggests that the less information is available *ex ante*, the higher the VOI should be. However, the impact on information value is unclear because increased uncertainty (i.e., less knowledge), affects the value of both the prior (equation 2.2) and informed (equation 2.5) decisions [Lawrence 1999].

Several studies focused on the effects of prior beliefs of decision makers on the value of information (e.g., Deutsch *et. al.* 2002, Schimmelpfennig and Norton 2003, Finkel and Evans 1987). For example, Deutsch *et. al.* [2002] investigate the value of information about the effect of climate change on thermocline circulation[2] (TCC) in the context of climate change policy. They consider hypothetical "optimistic" and "pessimistic" decision makers who assign low and high probability for possible TCC collapse respectively. The authors argue that the current system of ocean monitoring can have economic value for the "pessimistic" decision maker, but not for the "optimistic" one. The current frequency of ocean system observations is very low (once in one to three years). Hence, such monitoring system can not provide enough information to change optimistic beliefs about TCC collapse, even if they do not agree with the reality.

The value of information depends on the type of the data gathered. For example, Peck and Tiesberg [1995] and Nordhaus and Popp [1997] investigate the value of information about economic and biophysical parameters for green house gas policy. They show that information about economic parameters affecting environmental damage costs and abatement cost has higher value than the biophysical factors, such as temperature-CO_2 relationship, rate of decarbonization, and the atmospheric retention rate.

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[2] i.e., ocean water circulations caused by vertical temperature gradient

Another determinant of the information value is accuracy of information. Accuracy can be characterized as the probability of receiving an information signal y when the true state of nature is θ. Perfect information that precisely reveals the true state of the system has the highest value [Lawrence 1999].

Peck and Teisberg [1993] and Adams and Crocker [1983] find that the value of information is contingent on functional forms used in the payoff function F. Both studies show that the information about functional relationships in the system to be regulated has higher value that the information about specific parameters.

Abrahams and Shortle [1997] investigated the relationship between the value of information and regulatory instrument considered. They showed that it is the *ex ante* policy performance that determines the value of information for alternative instruments. The worse the *ex ante* policy performance is, the higher is the value of information.

Chapter 3. Methodology

This chapter describes environmental instruments and the information scenarios analyzed. Description of empirical model and experiments conducted conclude the chapter.

3.1. General Framework

The optimal economic design of a particular instrument maximizes the expected economic surpluses accruing to consumers, producers, and resource suppliers less environmental damage costs, subject to the distribution of farmers' responses to the policies being evaluated. Building on the model of Shortle *et. al.* [1998], assume a particular resource (e.g., a bay) is damaged by a single residual (e.g., nitrogen). Economic damages, D, are an increasing function of the ambient concentration of the residual, a, i.e. $D(a, \eta)$ with $D' > 0$, where η is a vector of imperfectly known environmental and economic parameters. Ambient pollution depends on loadings from agricultural nonpoint sources, g_i ($i = 1, 2, \ldots, n$), i.e., $a = a(g_1, g_2, \ldots, g_n)$. Loadings depend on a vector of variable inputs, x_i, and imperfectly known site-specific characteristics influencing fate and transport of pollution (e.g., in stream-loss parameters), ω_i. The relation for site i is $g_i = g_i(x_i, \omega_i)$.

Let $\pi_i(x_i, \delta_i)$ denote the economic returns to the ith farm, restricted on the vector of farm input use, x, and a vector of farm-specific characteristics, δ (e.g., the farmer's management ability). I assume that producers operate on competitive input and output markets, and take input and output prices as given. The vector of agricultural practice parameters, δ, is only private knowledge, i.e. management decision is made under asymmetric information. Given this specification, the expected social surplus is

$$ES = E\left[\sum_{i=1}^{n} \pi_i(x_i, \delta_i) - D\big(g_1(x_1, \omega_1), \ldots, g_n(x_n, \omega_n), \eta\big)\right] \qquad (3.1)$$

where the expectation operator E utilizes the planner's distributions of the unknown parameters.

I analyze the economic efficiency of two environmental policy instruments, price and quantity controls, applied to agricultural input use. The *ex ante* optimal *quantity controls* (x_i*) solves:

$$J^* = \max_{x_1, \ldots, x_n} ES = E\left[\sum_{i=1}^{n} \pi_i(x_i, \delta_i) - D\big(g_1(x_1, \omega_1), \ldots, g_n(x_n, \omega_n), \eta\big)\right] \qquad (3.2)$$

An optimal *price control* (e.g., tax/subsidy scheme) (t_i*) maximizes the expected social surplus (3.1) contingent on polluters' responses to the policy given their privately held information. Specifically, let

$$x_i(t_i, \delta_i) = \arg\max_{x_i}\{\pi_i(x_i, t_i) - t_i x_i\} \text{ for all } i = 1, \ldots, n \tag{3.3}$$

where x_i is a vector of agricultural inputs in ith watershed, and t_i is a vector of taxes/subsidies applied to input subset which directly influences pollution runoff (e.g., land and fertilizer). The optimal tax/subsidy scheme maximizes (3.2) subject to (3.3).

Given asymmetric information about pollution abatement costs, the ranking of the policy mechanisms will generally differ, with the results depending on properties of the underlying profit and damage costs functions [e.g., Weitzman 1974, Wu 2000]. The difference in the expected social surplus between price and quantity controls is expressed as $\Delta_{tx} = J_t - J_x \underset{<}{\overset{>}{=}} 0$, where the J_t refers to expected value of the price control, and J_x is the expected value of the quantity control. Δ_{tx} can be positive of negative.

Policy economic efficiency can be improved by collecting additional information to reduce or eliminate uncertainty about pollution control costs or benefits. The expected improvement in policy economic efficiency due to data gathering is the value of information. Since information collection is costly and the budget available for data collection is often limited, the value of information can help to target investment in research. For example, if the value of abatement cost information is higher than the value of other data types, and the costs are relatively low, collecting the control cost information can be the priority research direction. The data collection priorities are set before the actual data are gathered, and the *expected* effect of information on policy economic efficiency should be estimated. That is, the maximum social surplus should be calculated for every possible outcome of data collection, and then the results should be averaged given the probability of alternative findings. Hence, the value of information is the difference between the expected *ex post* and *ex ante* social surplus[3]. For example, the expected value of perfect information about δ under the quantity control is

$$VOI_{\delta}^{x} = E\left[\max_{x}\left(ES\left(x,\delta,\omega,\eta\right) \mid \delta\right)\right] - J_{x}^{*} \tag{3.4}$$

where the first term is the expected value of the optimal instrument contingent on realizations of δ, and the second term is the expected value of the decision without information (see (3.2)).

The value of information is contingent on the policy instrument. For example, given perfect information about pollution abatement costs, the optimized price and quantity mechanisms would perform the same: $\Delta_{tx} = 0$ if δ is known. Accordingly, the value of perfect information on producers will be greater for the instrument that provides the lesser expected social surplus value without that information.

The effect of policy spatial resolution on policy economic efficiency can be estimated by comparing expected economic efficiency of the spatially differentiated policies (3.1-3.3) with the economic efficiency of their uniform counterpart. Expected social surplus for the uniform policies can be estimated by solving the system (3.1-3.3) with additional constraints that the control level is the same for all polluters:

$x_i = x_j$ and $t_i = t_j$ for all i and j for quantity and price control respectively (3.5)

Historically, environmental regulation firstly targeted the most polluted spots or the most environmentally harmful activities. Such targeted approach decreases the

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[3] We assume that *perfect* information about each of the imperfectly known parameter is expected to be collected. That is, there is the true value of the parameter is revealed.

number of polluters to be regulated and achieves environmental improvement without considerable spending on contacting, monitoring, and enforcement. The expected economic efficiency of the targeted policy can be found by adjusting the policy level for the targeted polluter given that the activity level of the rest of the region is kept on the baseline level:

$$\begin{aligned} J^{p*} &= \max_{x_p} ES = E\left[\pi_p\left(x_p, \delta_p\right) + \sum_{i \neq p} \pi_i\left(x_{0i}, \delta_i\right)\right] - \\ &E\left[D\left(g_1(x_{01}, \omega_1), \ldots g_p(x_p, \omega_p), \ldots, g_n(x_{0n}, \omega_n), \eta\right)\right] \end{aligned} \tag{3.6}$$

where p indicates the most polluting producer.

Policy economic efficiency (3.1–3.3) and value of information (3.4) depend on the assumptions about the functional forms of model component π_i and D, and the distribution of random parameters used to estimate expected value E.

3.2. SRB

Eight subwatersheds of the SRB are in the model. The subwatersheds are based on the classification used in the PA State Water Plan. The plan identifies 12 subwatersheds (see Figure A2 and Table A1 in appendix A). Of the twelve, watersheds 223, 404 and 410 are dropped from this work because their nonpoint source loadings are negligible (see Table A1). Watershed 401 is combined with watershed 301, since the watersheds individually have negligible loading but lie in the interior of the SRB. I focus on nitrogen pollution loads from corn production. Corn production is the major source of nitrogen loading in the SRB, accounting for 30% of total nitrogen loadings delivered to surface water. This percentage rises even higher (approximately 67%) if atmospheric deposition is excluded [Abler *et. al.* 2001][4]. I model nitrogen loads as functions of nitrogen application and/or corn acreage in each subwatershed, and consider policy instruments that target these inputs.

3.3. Empirical Model

The research objectives are addressed using a numerical model of nitrogen pollution loads from agricultural nonpoint sources in the Pennsylvania portion of the SRB. The model includes three components that simulate pollution abatement costs, pollution transport processes, and water quality damage costs (see Figure A1 in appendix A). The *abatement cost* component simulates polluters' responses to different environmental policy designs and computes the corresponding profits and abatement costs. The *pollution transport* component simulates hydrological processes that drive transport of nitrogen runoff to the mouth of each sub-watershed and further to the Chesapeake Bay. Finally, the *water quality damage* component aggregates the processes that determine economic costs due to environmental pollution in the Chesapeake Bay region.

The performance of input-based quantity (tradable permits) and price (tax) instruments is evaluated against the expected net benefit criterion. The expected improvement in policy performance due to data gathering, that is the value of information, is estimated. The sensitivity of the policy performance and information value to the prior knowledge of the decision maker is examined by comparing the results for alternative functional forms of agricultural profits and alternative distributions of the

[4] Nonpoint sources are the leading cause of pollution in SRB and Chesapeake Bay [Chesapeake Bay Program 2003], and pollution from corn production is roughly 81% of all nonpoint nutrient loads [Carmichael and Evans 2000].

uncertain pollution transport parameters. Finally, the effects of two spatial policy characteristics on the policy performance and information value are examined: spatial differentiation (uniform versus differentiated regulation), and spatial targeting (number of sub-watersheds in the region targeted by regulation).

The current research builds on the models for agricultural and point source pollution controls previously developed by Abler, Horan, Shortle, and Carmichael (referred to below as the AHSC model) [see Abler *et. al.* 2001 and Horan *et. al.* 2002a, b]. The AHSC model has been used to examine the impacts of climate change on nitrogen loads from agriculture in the SRB, and the design of point-nonpoint nitrogen trading in the SRB. The AHSC models offer a useful starting point and the main features are retained. However, this research entails significant differences in the applications of the model. These differences include:

- An expanded scope of environmental policies: AHSC has only been used to examine point-nonpoint trading. I examine both price and quantity controls.

- Value of information: AHSC has not been used to estimate the value of information. Estimating the value of information requires computing and comparing *ex ante* and *ex post* optimal solutions. The AHSC model computes *ex post* optima but solution routine is substantially modified to compute *ex ante* optima.

- The AHSC model was used to represent differentiated regulation for each of the sub-watersheds. I am comparing performance of differentiated and uniform policies, as well as different levels of policy spatial targeting.

In addition, significant adjustments are made in the structure of the AHSC. These adjustments include:

- Functional forms. AHSC represents agriculture with 2-level CES production. I explore the sensitivity of study results to the assumption about agricultural production technology. Two specifications of production are used: 2-level CES production function and second-order series approximations of the unknown profit function.

- Alternative representations of information: The AHSC model captures certain parametric forms of aleatory and epistemic uncertainty, and asymmetric information. However, I wish to explore alternative representations of uncertainty. The AHSC model assumes specific probability distributions for each imperfectly known parameter. I explore how the relative ranking of policy instruments and value of information changes with assumptions on the prior probability distributions.

A description of the model components, the calibration procedure, the baseline data, and conducted simulations is presented below.

3.3.1. Control Costs

The optimal economic design of a policy instrument maximizes expected social surplus – the expected difference between benefits from economic activities and environmental damage costs [Just *et. al.* 1982]. The economic benefits are modeled as a sum of profits of the corn producers and the quasi-rent on the land market.

More explicitly, the corn production profit in each watershed is modeled as an increasing concave function of nitrogen fertilizer, land, and other inputs. The profit equation is defined below:

$$\pi_i(n_i, l_i, q_i, p_c, \rho_i, r_i, w_i, \delta_i) = p_c \cdot f_i(n_i, l_i, q_i, \delta_i) - \rho \cdot n_i - r_i \cdot l_i - w_i \cdot q_i, \tag{3.7}$$

where i indexes watersheds, n_i is nitrogen fertilizer applications to corn, l_i is land in corn, q_i is the vector of other agricultural inputs, p_c is the corn price, ρ_i is the fertilizer price, r_i is the land rental price, w_i is the vector of price for other inputs; f_i is corn production function, and δ_i is a vector of watershed-specific technical parameters. Fertilizer and land are modeled explicitly because they directly influence the amount of nitrogen runoff from a field and because of policy interest. Nitrogen applied as fertilizer is easily transported with soil particles or as a surface runoff. Land is often considered as a substitute to nitrogen fertilizer in agricultural production (extensive versus intensive agriculture) [see, for example, Mensbrugghe 2001]. Substitution of land for fertilizer in corn production process can lead to the reduction of the runoff without decrease in the production volume. In addition, the increase of the agricultural land use can be due to implementation of the best management practices (BMPs), such as vegetated buffer strips, which also decreases runoff.

The production parameters δ_i are determined by watershed-specific characteristics of land (e.g., land quality) and the management skills of the farmers (e.g., the timing of the fertilizer application). These are private knowledge of the farmers. To represent the asymmetric information, it is assumed that the farmers know δ_i when choosing a management practice, but the agency does not have these knowledge when choosing a policy.

Different functional forms can be assumed to model corn profit function (e.g., Constant Elasticity of Substitution (CES), Leontief, or translog production functions), and the parameter vector δ_i will vary accordingly. For example, CES function require specification of the input substitution elasticities and the factor shares, while the translog production function require knowledge of the coefficients near the logarithms of input uses and near the squares and cross-products of the logarithms. Given uncertainty about the true functional form, I consider two possible specifications – a quadratic approximation of the profit function and a profit based on CES production function. Parameter uncertainty is modeled in each case. Quadratic approximation implies that the production and profit functions are not known by the policy makers, and they are approximated by the second-order series expansion. CES production function implies that the authorities assume that this is the true specification of the production in the region, and they base the profit estimates on it. The functions will be described in more details in the next sections.

In the SRB corn competes with other agricultural and non-agricultural activities for crop land. To estimate policy-induced changes in land rental rates and related change in welfare of land owners, I model an agricultural land supply function, which is an increasing function of the agricultural land rent *r*:

$$l_i^S = l_i^S(r_i, \gamma_i), \qquad \frac{\partial l_i^s}{\partial r_i} > 0 \tag{3.8}$$

The land rental price can be found as the inverse function of land supply:

$$r_i = r_i(l_i^S, \gamma_i) \tag{3.9}$$

In the equilibrium, agricultural land supply equals land demand, and the superscript "*s*" can be dropped ($l_i^s = l_i^d$).

The functional form and the parameters γ_i of land supply are determined by the watershed-specific land as well as socio-economic processes influencing land allocation. The functional form is not perfectly known to the decision makers, and in the current research, the function is approximated by the first-order polynomial. The parameters γ_i are assumed to be perfectly observable by the land-owners, but not by the environmental agency.

The owners of the factors of production (including land-owners) derive "economic rent" from the services provided by the factors for which there is a positive market demand [Just *et. al.* 1982]. The land rent expression (3.9) can be used to compute the economic surplus accruing to land owners. The surplus (or quasi-rent, or producer surplus) is the area below the price line and above the supply curve [Just *et. al.* 1982]. In watershed *i*, the surplus on the land market (R_i) can be formally expressed as follows:

$$R_i = r_i l_i - \int_a^{l_i} r_i(z, \gamma_i) \cdot dz \tag{3.10}$$

where the low limit of integration *a* is the level of land supply for which land rent equals zero.

3.3.2. Pollution Fate and Transport

The environmental agency is unable to observe the pollution transport process at reasonable costs. However, it can form expectations conditional on relevant data. These expectations are viewed as the agency's estimate of pollution transport under specified circumstances [Shortle and Dunn 1986]. The general form of the agency's pollution transport model from *i*th watershed to the Bay is:

$$t_i = t_i(g_i, \omega_i) \tag{3.11}$$

where g_i represents NPS loading to the mouth of *i*th watershed; ω_i is a vector of watershed-specific parameters that determine how big is the share of pollution transported to the Bay, and t_i is the watershed's load to the Chesapeake Bay. To represent decision-makers' imperfect knowledge about transport processes, the parameter ω_i is modeled as a random variable.

Given watershed load (3.11), the total load from the SRB region to the Chesapeake Bay is the sum of load from each watershed:

$$L = \sum_i t_i \tag{3.12}$$

3.3.3. Economic Damages from Pollution

By definition, environmental damage cost is the damage which a pollutant or an activity causes to human health, agricultural crops, materials and ecosystems, expressed in monetary terms [Hanley *et. al.* 1997]. In the current study, environmental damage costs due to nitrogen pollution of the Chesapeake Bay are modeled with a single function. Essentially, the damage cost function combines two types of information: (1) *biophysical* information about reactions of water ecosystems to pollution and (2) *economic* information about effects of ecosystem's states on human well-being. As mentioned above, this approach does not require separate simulation of biophysical responses to pollution in the Bay, which significantly simplifies modeling task.

There are limited empirical estimates to determine the level of economic damages due to agricultural pollution in the Chesapeake Bay. Most of the studies [e.g., Sims and Coale 2002, Constanza *et. al.*1990] address ecological effects of the Bay pollution without considering economic consequences. Limited economic studies [e.g., Kirkley *et. al.* 1999, Bockstael *et. al.* 1995, Bockstael *et. al.* 1988] focus on specific well-defined services of the water system (e.g., angling), or examine site-specific case-studies (e.g., Neuse River in North Carolina) (see Table A2).

In the current research, the functional form of the damage is based on theoretical literature [e.g., Shortle 1984, Nawar 1998, Damania 2001, Kakita 2001, and Poe 1998] and practical considerations. It is generally assumed that the damage costs function has four intervals, where damages are zero (before assimilation potential limit is not reached), exponential (when the extra unit of emission causes more and more damages), and then concave and constant (when the degradation is very high, and an extra unit of emission can not worsen the situation further). Rising concern about the water quality shows that the assimilation potential of the Chesapeake Bay is exhausted. On the other hand, the water deterioration is still moderate – the estuary is still providing homes, protection and food for complex groups of species and the Bay is still a valuable commercial and recreational resource for the more than 15 million people who live in its basin [Chesapeake Bay Program 2003]. Hence, it is assumed that the current state of the Bay is on the second interval of the damage function (exponential). Such convex damage cost function guarantees that the objective function of the water quality manager – the social surplus – is concave with a single optimum level of emission.

The damage function is presented as an increasing convex function in pollution amount:

$$D = D(L,\kappa), \qquad \frac{\partial D\langle . \rangle}{\partial L} > 0, \qquad \frac{\partial^2 D\langle . \rangle}{\partial L^2} > 0 \qquad (3.13)$$

where κ is a vector of parameters. The convexity of the damage cost function implies that the marginal costs are increasing with increase in the pollution loads. To reflect the uncertainty about the damage costs, the parameter vector κ is assumed to be random.

3.3.4. Experiments Conducted

Four questions are addressed in the research: (1) the performance of NPS input-based price and quantity policies for different information structures, (2) the value of alternative information structures for the performance of alternative policies, (3) the effect of spatial scale and differentiation on policy performance, and (4) the importance of the prior decision maker's knowledge for policy ranking and information value. For the first question, price and quantity control are ranked based on their expected net benefits and given different information structures (see (3.1-3.3) above). I model five information scenarios. For the first scenario, I compare policies designed with the baseline (minimal, *ex ante*) information. In the other four scenarios, I analyze the expected increases in the policy performance due to improved information about: a) producers' abatement costs (parameters δ); b) pollution transport processes (parameters ω); c) environmental damage costs (κ); and d) all the above. The expected value of information is evaluated as the expected improvement in policy performance for scenarios a), b), c), and d) in comparison with the performance given baseline knowledge.

To analyze the sensitivity of policy performance and VOI to the prior knowledge of the decision maker, I compare the results assuming two probability distributions of the uncertain pollution transport parameters: uniform and normal.

All the experiments are conducted assuming the quadratic approximation of the agricultural profit function around the baseline values. However, to evaluate the sensitivity of the research results to this assumption, the performance of the quantity control mechanism is compared for two alternative functional form specifications: quadratic and constant elasticity of substitution.

To estimate the effect of spatial targeting on the policy performance and information value (equation 3.6), I model the policies affecting one, two, or three the most polluting watersheds, and compare their performance with the regulations applied to the whole region. The effect of the watershed targeting on the relative ranking of price and quantity instruments is analyzed.

The effect of policy spatial scale is examined by comparison of uniform and differentiated policies, as given in equation (3.5).

Chapter 4. Model Calibration

This chapter describes functional forms selected to simulate producers' profits, pollution fate and transport, and environmental damage costs. Data sources for calibration of deterministic and imperfectly known parameters also described. Then, simulation procedure is depicted.

4.1. NPS profits

I consider two possible specifications of the corn producer profit function: a second-order polynomial approximation around the baseline level of input use and the profit function based on CES production.

4.1.1. Quadratic approximation

The second-order series approximation (or expansion) of a function of two variables $z(x, y)$ and the approximation point (x_0, y_0) can be written as

$$z(x,y) \cong z_0 + \beta_1 \cdot (x - x_0) + \theta_1 \cdot (y - y_0) + \frac{1}{2} \cdot \left(\beta_2 \cdot (x - x_0)^2 + 2 \cdot \theta_2 \cdot (x - x_0) \cdot (y - y_0) + \Omega \cdot (y - y_0)^2 \right) \quad (4.1)$$

where z_0, β_1, β_2, θ_1, θ_2, and Ω are coefficients of approximation. An example of such approximation is Taylor expansion, which sets the coefficients β_1, β_2, θ_1, θ_2, and Ω equal to first- and second-order derivatives of the approximated function, and the constant z_0 equals to the value of the function at the point of approximation.

Series approximations are a common way to approximate a mathematical function, since the error of approximation can be easily controlled by the degree of the approximating polynomial, and the approximation is very easy to work with [Hosking *et. al.*1996]. However, the expansion polynomial closely reproduces the underlying function just in the "neighborhood" of the expansion point. The farther the independent variables from the expansion point is, the greater is the approximation error [Hosking *et. al.* 1996]. The approximation is widely used in production analysis (for example, [Hoff 2002] state that the translog form may generally be viewed as a second order Taylor approximation to an arbitrary production form).

In my analysis, for watershed *i*, the profits of corn producers are modeled by the restricted profit function $\pi_i(n_i,l_i) = k(n_i,l_i,\rho,r) - \rho n_i - r_i l_i$, where $k_i(n_i,l_i,\rho,r) = p_c \cdot f_i(n_i,l_i,q_i,\delta_i) - w_i \cdot q_i$ (see equation (3.7) above). I approximate $k_i(n_i,l_i,\rho,r)$ by a second-order polynomial. The expansion point used here is the baseline levels of fertilizer and land use. Given the approximation, the corn profit (3.7) can be written as:

$$\begin{aligned}\pi_i(.) \approx \pi_{i0} + \beta_{1i} \cdot (n_i - n_{i0}) + \theta_{1i} \cdot (l_i - l_{i0}) + 0.5 \cdot \beta_{2i} \cdot (n_i - n_{i0})^2 + 0.5 \cdot \theta_{2i} \cdot (l_i - l_{i0})^2 + \\ \Omega_i \cdot (n_i - n_{i0}) \cdot (l_i - l_{i0}) - \rho \cdot n_i - r \cdot l_i\end{aligned} \tag{4.2}$$

where π_{0i} is the profit before deducting the costs of land and fertilizer for the *i*th watershed, $\beta_i, \theta_i, \text{and}\, \Omega_i$ are approximation coefficients, and l_{oi} and n_{io} are the baseline levels of land and fertilizer use. The profit maximizing levels of fertilizer and land are then obtained by maximizing equation (4.2).

Coefficients β_{1i}, β_{2i}, θ_{1i}, θ_{2i}, and Ω_i are calibrated based on input prices and input demand elasticities in the following way. Assuming that the baseline values (l_{oi}, n_{oi}) are profit-maximizing choices (i.e. $\partial\pi_i/\partial n_{oi} = \rho_0$ and $\partial\pi_i/\partial l_{oi} = r_0$), it must be true that the coefficients before the linear terms in the equations are equal to the input prices: $\beta_{1i} = \rho_0$, $\theta_{1i} = r_0$. The coefficients before the square terms are calibrated to be the functions of own- and cross-price elasticities of input demands. To do this, nitrogen and land demands are found from the profit function (4.2):

$$n_i = n_{i0} + \frac{\Omega_i \cdot (r - r_0) - \theta_{2i} \cdot (\rho - \rho_0)}{\Omega_i^{\ 2} - \beta_{2i} \cdot \theta_{2i}} \tag{4.3}$$

$$l_i = l_{i0} + \frac{\Omega_i \cdot (\rho - \rho_0) - \beta_{2i} \cdot (r - r_0)}{\Omega_i^{\ 2} - \beta_{2i} \cdot \theta_{2i}}$$

From this input demand equations, one can express the own- and cross- price demand elasticities:

$$\varepsilon_n = \frac{\theta_{2i} \cdot \rho}{\theta_{2i} \cdot (\rho - \rho_0) - \Omega_i \cdot (r - r_0) + n_{i0} \cdot \left(\beta_{2i} \cdot \theta_{2i} - \Omega_i^{\ 2}\right)}$$

$$\varepsilon_l = \frac{\beta_{2i} \cdot r}{\beta_{2i} \cdot (r - r_0) - \Omega_i \cdot (\rho - \rho_0) + l_{i0} \cdot \left(\beta_{2i} \cdot \theta_{2i} - \Omega_i^{\ 2}\right)} \tag{4.4}$$

$$\varepsilon_{nl} = \frac{\Omega_i \cdot r}{\Omega_i \cdot (r - r_0) - \theta_{2i} \cdot (\rho - \rho_0) + n_{i0} \cdot \left(\Omega_i^{\ 2} - \beta_{2i} \cdot \theta_{2i}\right)}$$

where ε_l is the elasticity of land demand, ε_n is the elasticity of nitrogen demand, ε_{nl} is the cross-price elasticity of nitrogen demand to land price. Utilizing the relationships (4.4) and given the prices and inputs are set at their baseline values, we can express β_i, θ_i, and Ω_i as functions of the elasticities:

$$\beta_{2i} = \frac{\varepsilon_l \cdot l_{0i} \cdot r_0 \cdot \rho_o}{n_0 \left(\varepsilon_l \cdot \varepsilon_n \cdot l_{oi} \cdot r_0 - \varepsilon_{nl}^2 \cdot \rho_o \cdot n_{oi}\right)} \tag{4.5}$$

$$\theta_{2i} = \frac{\varepsilon_n \cdot r_0^2}{\varepsilon_l \cdot \varepsilon_n \cdot r_0 \cdot l_{0i} - \varepsilon_{nl}^2 \cdot \rho_0 \cdot n_{0i}} \tag{4.6}$$

$$\Omega_i = \frac{\varepsilon_{nl} \cdot r_o \cdot \rho_o}{\varepsilon_{nl}^2 n_{oi} \rho_o - \varepsilon_l \varepsilon_n r_o l_{oi}} \tag{4.7}$$

To capture the asymmetric information problem, the values of input demand elasticities are assumed to be uncertain from the regulators' perspectives. In other words, the values of the approximation coefficients β_{2i}, θ_{2i}, and Ω_i depend on the random elasticities, and are random themselves. The random expansion coefficients imply that environmental agency knows the points on the fertilizer and land input demand functions corresponding to the baseline prices and quantities (i.e. it observes prices and quantities), but does not know the slope of the input demand curves, nor how curves would shift with changes in the price of the other input.

To make the comparison between the two functional specifications – quadratic expansion and CES – easy, the values of input demand elasticities are selected to be the same for both functions.

4.1.2 Constant elasticity of substitution function

Alternatively, corn profit function can be modeled based on two-level CES function. The two-level CES function allows same/different substitution elasticities[5] for the inputs on the same/different levels of the function. In addition, the two-level CES have very convenient properties, which make it easy to work with. The production function is concave in inputs, which allows finding the input use level that maximizes the profits. The function exhibits constant return to scale, which implies constant marginal

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[5] The elasticity of substitution is defined as the percent change of in the input ratio compared to the percent change of the rate of technical substitution (the slope of the isoquant = F_x/F_y).

$\sigma \equiv \frac{d(x/y)}{d(F_y/F_x)} \cdot \frac{F_y/F_x}{x/y}$, where x and y areproduction inputs, and F represents a production function.

The elasticity of substitution is "a measure of the ease with which the varying factor can be substituted for others" [Hicks 1932 quoted by Fonseca and Ussher 2003]. For example, it can be used to analyze how much factor proportions change when the relative factor prices change, holding output constant [Collier 2003].

costs and linearity in output. In addition, the function is strongly separable, which implies that the allocation of factors within each class is determined exclusively by relative factor prices of that class only [Varian 1992]. Apart from the theoretical analysis, many empirical studies are based on the CES agricultural production (see, for example, Abler *et. al.* 2001, Horan *et. al.* 2002a, Howitt *et. al.* 1999, Thirtle *et. al.*1995, Salami *et. al.* 1998).

Following prior work based on this approach [Horan *et. al.* 2002a, Abler and Shortle 1995; Kawagoe *et. al.* 1985; Thirtle 1985; Binswanger 1974], production in the *i*th region, y_i, is a function of a composite biological input, B_i, and a composite mechanical input[6]:

$$y_i^* = \left(a_1 B_i^{*\alpha} + \left(1 - a_1\right) M_i^{*\alpha}\right)^{1/\alpha} \tag{4.8}$$

where y_i^*, B_i^*, and M_i^* are scaled levels of corn production and mechanical and biological inputs in *i*th watershed: $y_i^* = y_i / y_0$, $B_i^* = B_i / B_0$, and $M_i^* = M_i / M_0$; y_0, B_0, and M_0 are the baseline levels of corn production and factor use before the policy is imposed; a_1 is a distribution coefficient; and the exponent α is based on the elasticity of substitution between the inputs, σ_y:

$$\alpha = (\sigma_y - 1)/\sigma_y \tag{4.9}$$

The initial values of the normalized variables y^*, B^*, and M^* before environmental policy is imposed equal one.

[6] As stated in Sato [1967], to realistically describe a production process, "the production function must include a large number of factors representing various types of capital goods, labor, energy, intermediate materials, etc. However, a certain – and usually very substantial – degree of aggregation is essential in making such a production function operationally manageable. A number of inputs must be aggregated into a single index. Hence, we aggregate different types of capital goods into a composite good called capital. Similarly with labor, etc. The condition that must be satisfied for this kind of aggregation is the separability of variables".

In turn, on the second level of production, biological input consists of land and nitrogen fertilizer:

$$B_i^* = \left(b_1 \cdot n_i^{*\varsigma} + \left(1 - b_1\right) \cdot l_i^{*\varsigma}\right)^{1/\varsigma} \tag{4.10}$$

where $l_i^* = l_i / l_{i0}$ and $n_i^* = n_i / n_{i0}$ are normalized values of land and nitrogen use respectively, n_{i0} and l_{i0} are the baseline levels of input use; exponent ς is based on substitution elasticity between land and fertilizer, σ_B:

$$\varsigma = (\sigma_B - 1)/\sigma_B. \tag{4.11}$$

The mechanical input M_i combines labor, capital, and chemicals. The components of the mechanical input are not modeled explicitly, since the change in their proportions is not important for the purpose of the analysis.

In order to calibrate the distribution coefficients a_1 and b_1, two assumptions are made. First, it is assumed that the farmers' objective is to maximize profits. Given this assumption, the first order conditions for profit maximization with respect to the composite biological and mechanical inputs are:

$$y^*_B = a_1\, (y^* / B^*)^{1-\alpha} = w^*_B/p^* \tag{4.12}$$

$$y^*_M = (1 - a_1)\, (y^* / M^*)^{1-\alpha} = w^*_M/p^* \tag{4.13}$$

where w_B and w_M are composite prices of biological and mechanical inputs. Multiplying both sides of (4.12) and (4.13) by (B^*/y^*) and (M^*/y^*) respectively, one gets

$$a_1\, (y^* / B^*)^{-\alpha} = w_B B^* / p\, y^* \tag{4.14}$$

$$(1 - a_1)\, (y^* / M^*)^{-\alpha} = w_M M^* / p\, y^* \tag{4.15}$$

The second assumption made for the model calibration is the competitive equilibrium in the regional economy. In this case, the farms make zero economic profits, and gross returns from sales equal total costs:

$$p^* \, y^* = w^*_B \, B^* + w^*_M \, M^* \tag{4.16}$$

This assumption allows (4.14) and (4.15) to be rewritten

$$a_1 \, (y^* / B^*)^{-\alpha} = s_B \tag{4.17}$$

$$(1 - a_1) \, (y^* / M^*)^{-\alpha} = s_M \tag{4.18}$$

where s_B and s_M are biological and mechanical input shares in the total expenditures, $s_B = w_B \, B^* / (w_B \, B^* + w_M \, M^*)$ and $s_M = w_M \, M^* / (w_B \, B^* + w_M \, M^*)$. Note, that y^*, B^*, and M^* are the normalized levels of input use, and before a policy is imposed, their values equal one. Hence, the coefficient a_1 is the biological input cost share:

$$a_1 = s_B \tag{4.19}$$

By the same logic, the distribution coefficient b_1 in the composite biological input can be found from the nitrogen cost share, s_n:

$$b_1 = s_n / a_1 \tag{4.20}$$

To reflect the asymmetric information of decision makers about the polluters' production practice, the substitution elasticities σ_B and σ_y are modeled as random variables. However, in order to make the policy performance results comparable between the two production function specifications (CES and approximation), the imperfectly known substitution elasticities σ_B and σ_y are calibrated to determine the input demand elasticities ε_n, ε_l, and ε_{nl}. To derive the expressions for the input *demand* elasticities in terms of the input *substitution* elasticities, the following manipulations were performed. First, the expressions for input demand elasticities $n_i(\rho,r,w_M,a_1,b_1,\alpha,\varsigma,y)$, $l_i(\rho,r,w_M,a_1,b_1,\alpha,\varsigma,y)$, and $M_i(\rho,r,w_M,a_1,b_1,\alpha,\varsigma,y)$ for CES function are found from the following cost minimization problem:

$$\min_{n_i, l_i, M_i} \rho \cdot n_i + r \cdot l_i + w_M \cdot M_i$$

such that $\frac{y_i}{y_i^*} = 1 = \left(a_1\left(b_1\left[\frac{n_i}{n_{i0}}\right]^{\zeta} + b_1\left[\frac{l_i}{l_{i0}}\right]^{\zeta}\right)^{\alpha/\zeta} + a_2\left[\frac{M_i}{M_{i0}}\right]^{\alpha}\right)^{1/\alpha}$ (4.21)

(see appendix B for the solution). From these input demand equations, the elasticities $\varepsilon_n(\rho,r,w_M,a_1,b_1,\alpha,\varsigma)$, $\varepsilon_l(\rho,r,w_M,a_1,b_1,\alpha,\varsigma)$, and $\varepsilon_{nl}(\rho,r,w_M,a_1,b_1,\alpha,\varsigma)$ were evaluated as:

$$\varepsilon_x(.) = \frac{\partial x(.)}{\partial w} \cdot \frac{w}{x(.)} \tag{4.22}$$

where *x(.)* is nitrogen or land input demand function, and *w* stands for input price (see the complete expression in appendix B). The baseline input prices ρ, r, and w_M, as well the distribution parameters a_1 and b_1 are assumed to be known by the decision maker. By (4.9) and (4.11), the substitution parameters α and ς are functions of the input substitution elasticities, σ_B and σ_y. Hence, the value of the input demand elasticites are determined by input substitution elasticities $\varepsilon_n(\sigma_y, \sigma_B)$, $\varepsilon_l(\sigma_y, \sigma_B)$, and $\varepsilon_{nl}(\sigma_y, \sigma_B)$.

4.1.3. Land market

A first-order polynomial is used to approximate the imperfectly known land supply function in each of the sub-watersheds:

$$l_i \approx l_{i0} + \gamma_i \cdot (r - r_0) \tag{4.23}$$

Coefficient γ_i can be found utilizing expression for land supply elasticity ε_{ls}, given that the land use and land price are at the baseline levels:

$$\gamma_i = \varepsilon_{ls} \frac{l_{0i}}{r_0}, \tag{4.24}$$

The environmental agency's uncertainty about costs to land owners and policy reactions in land supply is modeled by treating the price elasticity ε_{ls} as a random variable with a known distribution from the agency's perspective. Essentially, I assume that agency knows a point on the land supply function in each watershed corresponding to the baseline price and quantity, but does not know the slope of the supply curves about the expansion point.

This land supply function can be used to compute the economic surplus accruing to land owners:

$$R_i = r_i l_i - \int_a^{l_i} \left(r_0 + \frac{1}{\gamma_i} \left(z - l_{0i} \right) \right) dz \tag{4.25}$$

The lower limit of integration *a* is the level of land supply for which land rent equals zero:

$$a_i = l_0 - \gamma_i r_0 \tag{4.26}$$

Combining (4.25) and (4.26), one can find the derive land rent function:

$$R_i = r_i l_i - \frac{\left(l_i - l_{i0} + \gamma_i \cdot r_{i0} \right)^2}{2 \cdot \gamma_i} \tag{4.27}$$

4.2. Pollution Transport to the Mouth of Sub-Watersheds

To simulate the nitrogen load from corn production to the mouth of each sub-watershed, an approximation of the Generalized Watershed Loading Function (GWLF) is used. GWLF was developed by Haith and Shoemaker [1987] and calibrated for SRB watersheds by Evans [2002-2003]. It is an empirically based model, which uses daily weather and water balance data to reproduce runoff volumes and nutrient loads. Surface nutrient losses are determined by applying dissolved N and P coefficients to surface runoff for each agricultural source area. The model allows multiple land use/cover scenarios, but each area is assumed to be homogenous with respect to parameters that determine the runoff (slope, land errosivity, etc). The model does not spatially distribute the source areas, but simply aggregates the loads from each area into a watershed total [Cousino 2002, Evans 2002-2003].

The GWLF is too complex to be directly linked with economic and damage components in my model. Accordingly, two simplifications of the GWLF were made. First, adopting the approach used in [Horan 2002a], regression of the GWLF predictions on the precipitation, nitrogen and land use was applied. In order to do this, the GWLF runoff predictions were received for alternative combinations of nitrogen, land, and precipitation in each watershed. Then, the regression coefficients and statistics were estimated for several specifications of the regression equations. The selected specification has the highest R squired (0.99), and hence, reproduces the GWLF results very closely [Carmichael and Evans 2000, Horan *et. al.* 2002a, b]. This specification is presented below:

$$g_i = A_i\left(\varphi_{1i} z_i^2 N_c l_i + \varphi_{2i}\left(z_i^2 N_c\right)^2 l_i + \varphi_{3i} z_i\right) \tag{4.28}$$

where g_i is the expected annual load; z_i is mean annual precipitation in the *i*th watershed; φ_{1i}, φ_{2i}, and φ_{3i} are regression coefficients; A_i is scaling (calibration) coefficient; N_c is nitrogen concentration in the agricultural runoff. Nitrogen concentration N_c is estimated as the ratio of nitrogen runoff mass ($(1-u)\, n_i$) and water runoff volume ($z_i\, l_i$):

$$N_c = \mu_i \frac{(1-u)(n_i / l_i)}{z_i} \tag{4.29}$$

here μ_i is a calibration coefficient, and u is the share of applied nitrogen which is taken (utilized) by the plants.

Combining (4.29) and (4.28), the following relationship between agricultural input use and pollution load is obtained:

$$g_i = A_i\left(\varphi_{1i} z_i \mu_i (1-u) n_i + \frac{\varphi_2 \left(z_i \mu_i (1-u) n_i\right)^2}{l_i} + \varphi_{3i} z_{3i}\right) \tag{4.30}$$

Equation (4.30) is highly nonlinear in nitrogen and land use, which seriously complicates the computation of the optimized expected social surplus. To overcome that problem, a quadratic expansion of the loading function (4.30) around baseline normalized land use level is used:

$$g_i \approx A_i\left(\varphi_{1i} z_i \mu_i (1-u) n_i + \frac{\varphi_2 \left(z_i \mu_i (1-u) n_i\right)^2 \left(3l_{0i}^2 - 3l_{0i} l_i + l_i^2\right)}{l_{io}{}^3} + \varphi_{3i} z_{3i}\right) \tag{4.31}$$

The resulting loading function is quadratic in the normalized input use, which simplifies the computations.

4.3. Pollution Fate and Transport to the Chesapeake Bay

The portions of deliveries in the *i*th watershed that ultimately reach the Bay are modeled using delivery coefficients, ω_i, so that the total delivered nitrogen loads from corn production to the Bay are:

$$L = \sum_i \omega_i g_i \tag{4.32}$$

where ω_i are pollution transport coefficients and g_i represents NPS loading to the mouth of *i*th watershed.

The coefficients of pollution transport (ω_i) are taken from U.S. Geological Survey's model called SPAtially Referenced Regressions On Watershed attributes (SPARROW) [US GS 2000]. The model relates in-stream water-quality measurements to spatially referenced characteristics of watersheds, including contaminant sources and factors influencing terrestrial and stream transport. A variety of factors affects pollution transport process, and following USGS suggestions [2000] model coefficients are represented by random variables.

4.4. Economic Damage Costs

A damage function is used to represent monetary losses due to nitrogen pollution of the Chesapeake Bay. The function is modeled to be exponential in pollution amount:

$$D = \psi \cdot L^{\tau} \qquad (4.33)$$

where ψ is a coefficient and the exponent τ is the elasticity of damage cost function. To reflect significant lack of knowledge about environmental damage costs, both parameters are represented by random variables. The variation in the exponent τ captures a part of uncertainty about the actual functional form of the damage costs. According to the interval selected for the parameter, the function can be quadratic, close to linear, cubic, or have a higher order.

Below, the sources of data for the model calibration are described. First, the deterministic parameters are discussed. Next, I describe how the uncertainties are modeled and the random variables are generated.

4.5. Baseline Data: Deterministic Parameters

4.5.1. NPS modeling

The data used to calibrate the model are reported in tables 3 – 5 in the appendix A. For the agricultural production, profit and the land supply functions, the data about input and output prices and baseline input use are necessary, along with the values of input substitution elasticities and CES distribution parameters. The baseline corn and input prices are reported in Table 3 in appendix A. Crop production is reported by county by PA Agricultural Statistical Service [2003]. To eliminate the stochastic effects of weather, five year average corn production data are used. To derive the watershed level of production, the distribution of a watershed lands between counties was used [Abler 2002][7]. Specifically, the base production in watershed i (y_i) is found as:

$$y_{0i} = \sum_m a_{mi} \cdot y_m \tag{4.34}$$

where i indexes watersheds, m indexes counties, a_{mi} denotes the share of the ith watershed area in the mth county.

Agricultural input use levels are based on the input shares in total expenditures and the input prices reported by [ERS 2003]. For example, nitrogen use is found from the nitrogen share s_n:

$$n_{i0} = \left(p_y y_{0i} s_n\right) / \rho \tag{4.35}$$

The input cost shares s_n, s_l and s_m are taken from on Economic Research Service (ERS) Cost and Return Survey (see Table A5) [ERS 2003]. The data are for the North-East region of the USA, and hence, they may not reflect the specific characteristics of SRB. However, this was the only source of data that estimate total expenditures in corn production, including both variable and fixed costs.

The environmental agency's uncertainty about producer's control costs and policy reactions is modeled by making coefficients and exponents in the corn profit and land

[7] An implicit assumption is that corn land is distributed between counties in the same fashion as the total watershed land.

supply functions random. Their variation is determined by the distributions of input demand and land supply elasticities and the input substitution elasticities, as discussed below.

4.5.2. Pollution transport process

To represent pollution transport process within sub-watersheds (equation 4.31), the following parameters are estimated: nitrogen concentration in agricultural runoff (N_c), mean annual precipitation (z_i), and regression coefficients (φ_i) (see Table A4 in appendix A). Following Abler *et. al.* [2001], precipitation data for the targeted watersheds were taken from [Teigen and Singer 1992]. Regression coefficients were provided by Horan [2002c]. The share of nitrogen utilized by plants u is assumed to be 0.7 [Musser *et. al.* 1995]. Average nitrogen concentration in the agricultural runoff for the region is $N_c = 7$ *mg/l* [Maryland Department of Natural Resources 1999, Evans 2002-2003]. To reproduce this nitrogen concentration value given the baseline nitrogen and fertilizer use, precipitation data and the share of nitrogen utilized by plants, a calibration coefficient μ_i is introduced into the equation (4.29). The value of another calibration coefficient A_i in the load function (4.28) is selected to replicate the annual NPS loading to the mouth of each sub-watershed as reported by Evans [2002-2003]. Following USGS suggestions, coefficients of pollution transport to the Chesapeake Bay (ω_i) are modeled as random variables and are discussed below.

4.6. Imperfectly Known Parameters

The model captures three aggregated sources of uncertainty in environmental policy-making: imperfect knowledge of abatement costs, pollution transport, and damage costs. Uncertainty is modeled by making parameters of the abatement, transport and damage cost functions random. The distributions of the random parameters are based on readily available literature sources. Given that every decision maker has an access to these literature sources, minimal information available to decision-makers is modeled.

There has been little research on the structure of agricultural production and agricultural land markets in SRB, and the region does differ substantially from other regions of the US. Accordingly, beyond the restrictions imposed by economic theory, there is substantial ignorance about the corn production and land parameters. To reflect capture part of this uncertainty, the values of input substitution elasticities in the CES production function are assumed to be uncertain from the regulator's perspectives with the range based on the literature for other regions [Abler *et. al.* 2001]. Uniform distribution is utilized to reflect large degree of uncertainty associated with the parameters. For each possible substitution elasticity value used in CES corn production function, there is a corresponding value of the input demand elasticities used in the quadratic approximation of the corn profit function. The input substitution and demand elasticities are checked to satisfy the requirements for negative slope of the input demand with respect to own prices and concave profit function ($\beta_{2i} < 0$, $\theta_{2i} < 0$, and $\beta_{2i}\, \theta_{2i} - \Omega_i^2 > 0$). To have positively sloped input demands with respect to the price of the input-substitute, I select the elasticity values to make Ω_i negative. The values that did not meet the requirements were discarded. The land supply elasticity, γ, is selected based on theoretical recommendations [Abler *et. al.* 2001]. Land supply is inelastic, hence the elasticity values from 0.1 to 0.9 are considered. Again, there is a large degree of uncertainty about the land supply elasticity, and the uniform distribution for γ is utilized.

I also use a uniform distribution for the damage cost parameters. The damage cost elasticity is selected to make the damage function convex (elasticity is greater than one). On the other hands, the total damage costs are limited to be reasonably low and not to drive farmers out of the market, and the maximum elasticity is selected to be three. The range of the possible values for the damage costs coefficient is selected in such a way that the *ex ante* model solutions for quantity mechanism reproduces the optimal loads defined in the Chesapeake Bay agreement and by US GS. Initially, the states in the Chesapeake Bay made a commitment to reduce nitrogen loading to the Bay by 40% by the year 2000 [Chesapeake Bay Program 2003]. However, this objective was not achieved. Belval and Sprague [1999] report that "the flow-adjusted concentration of total nitrogen decreased about 12 to 25 percent at the Susquehanna River monitoring station during 1985-98. The unadjusted concentration of total nitrogen also decreased about 20 percent". Given this information, the upper bound of the damage cost coefficient is selected to have the optimal load to the Chesapeake Bay L be 60% from the baseline level (under the quantity policy). The lower bound of the coefficient is selected to produce 20% load reduction under the *ex ante* quantity control.

In contrast to the lack of information for assessing abatement costs and damage costs, there has been substantial research on the transport of nitrogen in the SRB. We use pollution transport coefficients based on the USGS SPARROW model [Abler *et. al.* 2001, Carmichael and Evans 2000], and assume normal distribution for the parameters. The variance for the distribution is based on [USGS 2003]. The values of the transport coefficients that were greater than one or smaller than zero were thrown away. To estimate the effect of initial knowledge about the system on policy ranking and information value, we compare the results for uniform and normal distributions of the transport coefficients.

The amount of information available about each uncertain parameter is characterized by the variance and entropy (see table A7 in appendix A). The damage cost elasticity has the highest uncertainty; while the damage costs coefficient is happen to have the lowest uncertainty.

4.7. Preliminary analysis

The value of information is high if the policy outcomes and optimal decision depend on the values of imperfectly known parameters [Lawrence 1999]. For example, the data about environmental damage costs determine how strict the environmental regulation should be. Low damages lead to a soft policy with low pollution control costs, while high damage estimate result in a strict regulation with significant abatement costs and sizeable damage costs prevented. Thus, it can be expected, that the value of damage cost information is high. The value of information can also be high if there is significant uncertainty in the value of a relevant parameter [Lawrence 1999]. For example, the value of perfect information about private pollution control costs can be expected to be higher for the case when the estimates range from \$5 to \$500 per unit of emission reduction than for the estimates of \$5 to \$10 per unit.

The sensitivity of policy decisions to the values of imperfectly known parameters is analyzed based on a deterministic social surplus function (DSS). The DSS is constructed by setting all imperfectly known parameters in social surplus to their mean values. Then, the function is maximized with respect to nitrogen and land use. Deterministic net benefits (DNB) are estimated as the difference in the DSS for the baseline and optimized levels of the inputs. Then, I estimate the change in the optimized DSS and DNB due to 50% alteration in each of the uncertain parameters. This change is used as an indicator of the decision sensitivity to the values of uncertain parameters. This analysis is performed for both specifications of the corn profit function. The results are presented in the table below.

The increase in damage costs elasticity in comparison with its mean value results in a large change of the DSS and DNB for both specifications of the agricultural profits (see table 4.1), and, hence, the value of damage cost information is expected to be high. In the model, the elasticity is the exponent of the damage cost function. The increase in the exponent makes the environmental damages higher for every pound of the nitrogen load. In addition, it makes the marginal damages increase more rapidly. As a result, even a small deviation from the optimal level of regulation results in significant losses in environmental quality. The effect is more significant for the DSS based on quadratic approximation of the corn profits, which suggests that value of the data can be higher for this specification.

Among other parameters, the land supply elasticity significantly influences the DSS and DNB. The elasticity is an important parameter of the pollution abatement costs, which affects both the corn production profits and the surplus on the land market. Consider a quantity control, which leads to an increase in the land demand. Rise in the land supply elasticity decrease the responsiveness of land prices to the increase in land demand. Hence, the policy-induced increase in demand is not associated with significant increase of the costs of corn producers and can lead to rise in their profits. On the other hands, decrease in the elasticity makes land supply prices very sensitive to changes in quantities demanded, resulting in significant increase in costs of corn producers from increased quantities of land use.

Table 4.1. Sensitivity of the Optimized DSS and NB to 50% Change in the Values of Uncertain Parameter Values (Percent, %)

Parameter	Notation	Quadratic approximation of agricultural profit function		CES agricultural production function	
		DSS	NB	DSS	NB
Substitution elasticity between nitrogen and land in CES, increase or decrease	σ_{NL}	NA*	NA*	< 1	< 1
Substitution elasticity between composite mechanical and biological inputs, increase or decrease	σ_{MB}	NA*	NA*	< 1	< 1
Nitrogen demand elasticity in quadratic expansion of profit function, increase or decrease	ε_N	< 1	< 1	NA*	NA*
Land demand elasticity in quadratic expansion of profit function, increase or decrease	ε_L	< 1	< 1	NA*	NA*
Nitrogen demand elasticity, cross-price, in quadratic expansion of profit function, increase or decrease	ε_{NL}	< 1	< 1	NA*	NA*
Land supply elasticity	ε_{LS}	+/- 16.7	<1	+/- 16.7	+100% for increase, -22.9% for decrease
Coefficient of the damage function, increase or decrease	$\omega_1 - \omega_8$	< 1	< 1	< 1	< 1
Each of the pollution transport coefficients, increase or decrease	ψ	< 1	< 1	< 1	< 1
Damage cost elasticity	τ				
• Increase		-51.3	>100%	-37.7	-33%
• Decrease		< 1	<1	< 1	< 1

* In the sensitivity analysis, I do not account for the link between agricultural input demand and input substitution elasticities for the two functional forms of the corn profit function considered.

Other uncertain parameters do not significantly alter the values of DSS and DNB in these settings; however, the value of the data about their true value can still be high.

To show this, I estimated the sensitivity of the DSS and DNB in slightly different settings. Now, the DSS is constructed and the DNB is estimated given the maximum damage costs elasticity, while other parameters are still held on their mean values. The results are presented in Table 4.2.

Table 4.2. Percent Change in the Optimal DSS and NB, Given Damage Cost Elasticity is Maximum and Other Parameters are on the Mean Values

Parameter	Notation	Quadratic approximation of agricultural profit function		CES agricultural production function	
		Percent change in the SS based on	Percent change in NB	Percent change in the SS based on	NB
Nitrogen and land substitution elasticity for the CES corn production function,	σ_{NL}	NA*	NA*		
• Increase				+12.1	+10.5
• Decrease				-12.1	-18.2
Substitution elasticity for biological and mechanical inputs in CES corn production function,	σ_{MB}	NA*	NA*		
• Increase				<1	<1
• Decrease				<1	<1
Nitrogen demand elasticity for the quadratic corn profit function,	ε_{N}				
• Increase		-66.2	-4.6	NA*	NA*
• Decrease		+26.5	+1.8	NA*	NA*
Land demand elasticity for the approximated corn profit function,	ε_{L}				
• Increase		-1.5	<1%	NA*	NA*
• Decrease		+1.0	<1%	NA*	NA*
Nitrogen demand elasticity with respect to land price for the quadratic corn profit function,	ε_{NL}				
• Increase		-9.1	+0.3	NA*	NA*
• Decrease		+4.0	-0.6	NA*	NA*
Land supply elasticity,	ε_{LS}				
• Increase		-62.5	-0.4	-22.4	-46.0
• Decrease		+28.5	+0.2	+22.3	+145.5

Parameter	Notation	Quadratic approximation of agricultural profit function		CES agricultural production function	
		Percent change in the SS based on	Percent change in NB	Percent change in the SS based on	NB
Pollution transport coefficient, watershed 202,	ω_1				
• Increase		-2.2	+22.8	-1.5	-1.1
• Decrease		+4.9	-24.2	+2.8	+2.2
Pollution transport coefficient, watershed 204,	ω_2				
• Increase		-10.2	+35.0	-5.9	-4.4
• Decrease		+19.0	-37.4	+10.6	+8.3
Pollution transport coefficient, watershed 207,	ω_3				
• Increase		-6.1	+28.2	-6.1	-2.6
• Decrease		+8.8	-23.8	+5.1	+3.8
Pollution transport coefficient, watershed 214,	ω_4				
• Increase		-1.7	+10.2	-1.0	-0.8
• Decrease		+3.1	-10.3	+1.7	+1.3
Pollution transport coefficient, watershed 215,	ω_5				
• Increase		-3.7	+16.2	-2.2	-1.6
• Decrease		+4.8	-12.4	+2.6	+2.1
Pollution transport coefficient, watershed 302,	ω_6				
• Increase		-1.9	+10.0	-1.1	-0.9
• Decrease		+3.3	-10.0	+1.8	1.5
Pollution transport coefficient, combined watershed 301+ 401,	ω_7				
• Increase		-11.6	+18.4	-7.5	-4.4
• Decrease		+12.1	-16.3	+7.5	+5.0
Pollution transport coefficient, combined watershed 402,	ω_8				
• Increase		-4.0	+11.9	-2.5	-1.6
• Decrease		+4.9	-11.0	+2.9	+2.0
Damage cost coefficient	Ψ				
• Increase		-14.1	+52.7	-8.5	-5.9
• Decrease		+21.9	-52.1	+12.8	+9.5

[*] In the sensitivity analysis, I do not account for the link between agricultural input demand and input substitution elasticities for the two functional forms of the corn profit function considered.

For the maximal damage cost elasticity, the sensitivity of the DSS and DNB to the values of transport coefficients, input demand and substitution elasticities, as well as damage costs coefficient increases. Hence, collection of data about each of the parameter can significantly improve policy performance.

The damage cost elasticity (i.e., exponent of the function) can be interpreted as the determinant of the functional form of the damage costs, e.g., linear, quadratic, or cubic. The increase in DSS and DNB sensitivity with rise in the damage cost curvature indicates the importance of the knowledge about the true functional forms for estimating information values.

The DNB are negligible for the case when all the parameters are set on their mean values. These estimates fail to account for the significant effect of variation in the damage and abatement cost parameters on the regulatory outcome. Hence, the results of the deterministic analysis based on the mean values can not be used to guide the policy decisions.

4.8. Simulations

The terms in the expression for the expected social surplus (3.2) are highly nonlinear with respect to the uncertain parameters, which makes it difficult to compute the expected value of the social surplus analytically. Three methods of numerical approximation of the expected value were considered: Monte Carlo, Latin Hypercube, and Gaussian quadrature. The Monte Carlo method involves calculating the expected value as a sample mean of the function [Rubinstein 1981]:

$$\int_{\theta}\int_{\eta}\left[f(x,\theta,\eta)\cdot d\theta\cdot d\eta\right]\approx\frac{1}{M}\sum_{m=1}^{M}f(x,\theta_m,\eta_m) \tag{4.36}$$

where $f(x,\theta,\eta)$ is an arbitrary function of a variable x and two random parameters θ and η, and M is the sample size (i.e., the number of distinct values of the random parameters θ

and η analyzed). The method is conceptually simple and theoretically sound [Bobba *et. al.* 2000, Hession *et. al.* 1996, Kao and Hong 1996]. It allows statistical evaluation of the effects caused by uncertainties on the basis of the distribution of simulation results. For each sample size M, it is possible to estimate the confidence interval around the approximation (4.36), which includes the true value of the integral [Bobba *et. al.* 2000, Hession *et. al.* 1996, Kao and Hong 1996]. The only disadvantage of the method is the large sample size required for reliable approximation, which implies long computer running time.

Latin hypercube procedure is based on the same principle of approximation as Monte Carlo (equation (4.36)). However, instead of drawing the values of parameter θ_m and η_m randomly¸ the method involves the division of the parameters' distributions into intervals, then paring the intervals from different distributions in random manner, and finally, drawing one random sample from each set of intervals. In this way, it is insured that the whole range of random parameter values is covered even with a small sample size [Nordhaus and Popp 1997].

Gaussian quadrature estimates an integral of a function *f(x)* as a sum of the function values for M points x, η_m multiplied by the weights c_m [Srivastava 2002]:

$$\int_{\eta} f(x,\eta)\cdot d\eta = \sum_{m=0}^{M} c_m \cdot f(x,\eta_m) \tag{4.37}$$

The weights c_m and the points (x, η_m) are selected to make the approximation exact when the function *f(.)* is a polynomial of the order (2 n – 1) or lower [Srivastava 2002]. The approximation is very easy to use and allows close approximation of a function with a very small sample size. However, when the function is very nonlinear and involves many random parameters, if is getting difficult to find the weights c_m for the approximation.

After comparison of the methods, the Monte Carlo approximation was selected. Although the Latin hypercube allows accurate approximations with much smaller sample size, the current model has an extra complication, which prohibits using the method. The draws of imperfectly known parameters (such as input substitution and demand elasticities) are required to satisfy extra conditions (such as concavity of the agricultural profit function and negativity of the slopes of input demand). These extra requirements complicate the random pairing of the parameter draws required for Latin hypercube. In addition, for several draws of random variables, the objective function (4.2-4.3) becomes very flat, and the optimization program fails to find a solution. This means that some ranges of parameter values are will not be in the Latin Hypercube approximation. The Gaussian quadrature was rejected because the model includes 12 random parameters[8] and 16 independent variables[9], which makes selection of the weights c_m and estimation points η_m very is complicated.

Based on the Monte-Carlo approach, I compute the expected social surplus (3.2) as the sum of the social surplus values for randomly drawn values of the uncertain parameters divided by the total number of draws M:

$$ES(x_1,\ldots x_8) \approx \frac{1}{M}\sum_{m=1}^{M}\left[\sum_{i=1}^{8}\pi_i(x_i,\delta_{im},\gamma_{im}) - D(g_1(x_1,\omega_{1m}),\ldots,g_8(x_8,\omega_{8m}),\kappa_m)\right] \quad (4.38)$$

For the baseline information scenario (a), the policy performance is computed by maximizing the ES (4.38) with respect to the policy choices x^* or t^* subject to the farmers' responses to the policies (see equations 3.2 – 3.3):

[8] This number includes 2 damage cost parameters, 8 transport coefficients, and 2 input substitution elasticities. There are more random parameters in the model. However, some of them can be expressed in terms of others, e.g., input demand elasticities can be expressed as functions of input substitution elasticities.

[9] Two inputs (nitrogen and land) in each of the sub-watershed

$$J^* = \max_{x_1,\ldots,x_8} ES \tag{4.39}$$

For the other information scenarios (b - d), I calculate the expected social surplus as an average of the optimal performances of the policies designed with information. For example, the expected policy performance for the scenario with abatement cost, transport, and damage cost information is:

$$J^{**} = \frac{1}{M}\sum_{m=1}^{M} \max_{x_{1m},\ldots,x_{8m}} \left[\sum_{i=1}^{8} \pi_i(x_i, \delta_{im}, \gamma_{im}) - D(g_1(x_1, \omega_{1m}),\ldots, g_8(x_8, \omega_{8m}), \kappa_m) \right] \tag{4.40}$$

where j indexes randomly drawn values of abatement cost parameters.

The sample size M was selected to produce the policy performance results which do not depend on the sample size. For the baseline information scenario (a), six sample sizes were analyzed: M = 100, 200, 500, 1000, 1500, 3000 and 5000 (see Table A8). The discrepancies between the results for M = 1500, M = 3000 and M = 5000 were approximately 1%. I choose the sample size M = 1500 for all scenarios. For scenarios (b) through (d), the 95% confidence intervals are calculated to acknowledge the possible deviation of the true values of the expected social surplus from the estimate. The confidence interval is estimated as the mean of the optimal ES values plus/minus the product of the estimated standard deviation s_M and the t-value [Lane 2001]: $J^{**} - t \cdot s_M \le J^{**} \le J^{**} + t \cdot s_M$.

Several programming languages were tried for computing the model: Mathematica (version 4.2), GAUSS (version 3.22), MatLab (version 12), and Borland C++. GAUSS 3.22 (Advanced Mathematical and Statistical System; Aptech 2003) was selected because of: a) very powerful in-built constrained optimization routine, which allows nonlinear constraints and objective function (e.g., Mathematica works best only with linear constraints); b) relatively small time of computing (both MatLab and Mathematica are much slower); c) simplicity of debugging the programs (for comparison, it is more difficult to debug a program in Borland C++). However, Mathematica has random number generators for different types of distributions, while GAUSS can generate random numbers only from standard normal distribution and uniform distribution on [0, 1] interval. So, the samples of random variables were generated in Mathematica.

Chapter 5. Results

This chapter presents the results for: a) the efficiency of nitrogen and land use taxes and aggregate trading quotas given alternative uncertainty structures; b) the value of alternative types of information for the alternative policy instruments; c) the effects of spatial scope (number of watersheds regulated) and differentiation on expected policy performance and information value; and d) the effects of the initial knowledge of decision-makers on the policy efficiency and information values.

The optimal level of taxes and quotas on the land and fertilizer use depend on the structure of uncertainty facing the decision maker, and the assumption about the functional relationships between economic and biophysical parameters in the region. For the social surplus (SS) with *quadratic* corn profits, *optimal taxes* on nitrogen reach up to +300% of the price across alternative information scenarios and values of the uncertain parameters. Land can be subsidized for up to 500% of the baseline price. *Optimal* aggregate fertilizer *quota* is lower than the baseline level of nitrogen use. On the contrary, the optimal aggregate land use quotas are higher than the watersheds' baseline land use. Across alternative information scenarios, the fertilizer use can be required to be decreased by up to 70%, and land use quotas can be up to 30% higher than the baseline land use. High land use quotas and subsidies are due to the assumptions that land and fertilizers are substitutes in the production process, and hence, increase in the land use can decrease the fertilizer application without decline in producers' profits. In addition, an increase in the land use given fixed/reduced fertilizer application lessens the average rate of nitrogen use per acre. As a result, average runoff per acre also decreases.

Just the quantity control is analyzed for the SS function based on CES corn production. Both land and nitrogen uses decreases after policy imposition in comparison with the baseline level. However, the reduction in nitrogen use is more significant than the decrease in land use. Depending on the realized values of the imperfectly known parameters across alternative information scenarios, nitrogen use declines by up to 50%, while the land increases by at most 30%.

5.1. Relative Policy Ranking

The relative policy ranking is affected by numerous characteristics of environmental and economic systems, and, in general, can not be analyzed analytically. The empirical analysis of nitrogen- and land-use based policies in SRB is summarized in Table 5.1 below. The expected net benefits for the alternative policy mechanisms (rows) and information scenarios (columns) are presented. Expected net benefits (ENB) are estimated as a difference between expected social surplus with and without regulations.

Land and fertilizer taxes outperform the quantity controls for the baseline (*ex ante*) information set by \$1.5 million (12% of expected net benefits for the quantity controls). The taxes also dominate the quantity controls for the pollution transport information scenarios (the difference in expected net benefits is 11.1%). The mechanisms perform the same is abatement costs (or *ex post*) information is expected to become available. With improved damage costs information, the difference in policies' expected net benefits is not statistically significant.

Table 5.1. Net Benefits for Alternative Policy Regimes, in million dollars

	Information scenarios				
	Ex ante	**Pollution transport**	**Abatement costs**	**Damage costs**	***Ex post***
Input quantity controls	12.3	12.6	13.7	19.2	20.1
95% confidence interval		12.5-12.6	13.2-14.2	18.6-19.7	19.4-20.8
Input taxes	13.8	14.0	13.7	19.3	20.1
95% confidence interval		14.0-14.1	13.2-14.2	18.7-19.9	19.4-20.8
Difference between the policies	1.5	1.4	0	Not statistically significant	0

The different expected net benefits for the mechanisms are due to the economic responses of the polluters to the alternative management schemes. With the quantity control, the aggregate level of land and fertilizer use for a watershed *can not* be adjusted. In contrast, with input taxes, the level of fertilizer and land use *is* adjusted among watersheds according to the privately held production profit information. The redistribution of the load reductions among watersheds given tax regulation decreases the impact of pollution management on the producers' profits. On the other hand, this adjustment makes the environmental outcome of the policy more uncertain. For the quantity control, the variation of environmental damages is due to the uncertainty in the pollution transport processes. For the price control, the imperfect knowledge of the polluters' choices also contributes to the variation in the policy environmental impact. In current research, the benefits of increased variability (in terms of expected producer profits) outweigh the costs of increased variability (in terms of expected damages) causing expected social surplus to be higher for the tax control than for the quantity control.

The same performance of the instruments for abatement costs and complete information scenarios is in line with the Weitzman [1974] results.

5.2. Value of Information

The study shows that information increases the expected net benefits of environmental policies. However, the increase depends on the type of information collected and on the policy mechanism used.

The value of information for alternative policy instruments and information types is summarized in table 5.2. The value of information is measured in absolute terms (million dollars) and in percents with respect to the *ex ante* expected net benefits for the respective instruments. The value of information in absolute terms is simply the difference in expected net benefits between the given scenario and the *ex ante* scenario.

Table 5.2. Expected Value of Information, million dollars and (percents)

Policy instrument	**Information scenarios**			
	Pollution transport	***Abatement costs***	***Damage costs***	***Ex post***
Input quantity controls	0.3 (2.4)	1.4 (11.4)	6.9 (56.1)	7.8 (63.4)
Input taxes	0.2 (1.4)	close to zero (close to zero)	5.5 (39.9)	6.3 (45.7)
Difference	0.1	1.4	1.4	1.5

First, let me consider the value of information by data type. The perfect damage cost information has the highest value for both policy mechanisms. This information is expected to improve the policy performance by 56% (for the quantity controls) and 40% (for land and fertilizer taxes). As suggested in the preliminary analysis in the previous chapter, the significant information value can be due to a high sensitivity of policy decisions to the damage cost elasticity, as well as large uncertainty associated with the parameter (see entropy values in Table A7).

The value of the damage cost information can also be influenced by the values selected for abatement cost parameters. Table 5.3 summarizes an experiment where the damage cost information was estimated given deterministic abatement costs and the pollution transport coefficients and quadratic corn profits. The information value increases with the increase in nitrogen demand elasticity and decrease in land supply elasticity. Although these results were computed for a very small sample n = 100, which is not enough to account for all possible values or random parameters, this analysis still shows that the value of damage cost information is conditional on abatement cost parameters.

Table 5.3. Effects of 10% change in the Land and Fertilizer Demand and Supply Elasticities on the Damage Cost Information Value (Sample Size = 100)

Parameter	Notation	Percent change in the value of damage cost information
Nitrogen demand elasticity,	ε_N	
• **Increase**		+22.5
• **Decrease**		-27.5
Land demand elasticity, Increase or Decrease	ε_L	<1
Nitrogen demand elasticity with respect to land price,	ε_{NL}	
• **Increase**		+4.7
• **Decrease**		+1.9
Land supply elasticity,	ε_{LS}	
• **Increase**		-3.5
• **Decrease**		+16.4

Now let me consider how the policy mechanism affects the value of information. This difference is presented in the final row (labeled *Difference*) in Table 5.2. Information has higher value for the quantity controls than for the tax controls. This can be examined in line with research by Abrahams and Shortle [1997]. The mechanisms perform the same given perfect information. Hence, by definition, the VOI is higher for the mechanism that performs worse *ex ante*. In other words, the same factors that influence the *ex ante* policy performance, determine the difference in the information value.

For the quantity control, the abatement cost information has higher value than the pollution transport data while for the input taxes the ranking is reversed. The result emphasizes that the information collection priorities should be contingent on the management option considered.

The model used in the research is nonlinear; it involves many interrelated economic and biophysical parameters. This complexity does not allow more detailed study of the VOI determinants. Further investigation is required to explain the differences in the VOI for the mechanisms.

5.3. Policy spatial scope: the number of watersheds regulated

Transaction costs associated with policy monitoring and enforcement can be reduced by the decrease of the geographic scope of a policy, i.e., regulating a subset of watersheds instead of the whole region. However, decrease in the policy spatial scope reduces policy efficiency. Below, the differences in the policy efficiency are analyzed for the regulation of the entire SRB region, or just one, two, or three SRB watersheds. The watersheds targeted by regulation (i.e., the policy spatial scope) are chosen based on the loadings to the mouth of each watershed. That is, the watersheds are divided into "more polluting" and "less polluting" types, and the "more polluting" watersheds are regulated first. The expected net benefits for quantity and tax controls are summarized in Tables 5.4 and 5.5.

Table 5.4. Expected Net Benefits for Quantity Controls with Different Spatial Targeting, million dollars

Watersheds	Information scenarios				
	Ex ante	*Pollution transport*	*Abatement costs*	*Damage costs*	*Ex post*
8	12.3	12.6	13.7	19.2	20.1
95% confidence interval		12.5-12.6	13.2-14.2	18.6-19.7	19.4-20.8
3	9.6	9.8	10.9	16.4	17.5
95% confidence interval		9.7-9.9	10.4-11.4	15.4-17.3	16.5-18.5
2	6.9	7.1	8.1	13.3	14.4
95% confidence interval		7.0-7.2	7.6-8.6	11.9-15.8	13.0-15.9
1	4.3	4.5	5.2	9.4	10.3
95% confidence interval		4.4-4.6	4.7-5.7	7.4-11.5	9.2-11.5

The increase in the scope of environmental control from the most polluting to less environmentally harmful watersheds increases the expected net benefits, but at a decreasing rate. In the model, regulation of one the most polluting watershed contributes approximately 40% of total expected net benefits from regulation in the region, and the management of three the most polluting watersheds accounts for about 80%. These percents are almost the same for both policy mechanism and the information scenarios.

Table 5.5. Expected Net Benefits for Tax Regulations with Different Spatial Targeting, million dollars

Watersheds	Information scenarios				
	Ex ante	*Pollution transport*	*Abatement costs*	*Damage costs*	*Ex post*
8	13.8	14.0	13.7	19.3	20.1
95% confidence interval		14.0-14.1	13.2-14.2	18.7-19.9	19.4-20.8
3	11.1	11.4	10.9	15.6	17.5
95% confidence interval		11.4-11.5	10.4-11.4	14.4-16.7	16.5-18.5
2	8.3	8.5	8.1	11.2	14.4
95% confidence interval		8.5-8.6	7.6-8.6	9.4-12.9	13.03-15.9
1	5.5	5.6	5.2	8.6	10.3
95% confidence interval		5.7-5.7	4.7-5.7	6.3 -10.9	9.2-11.5

The low-polluting watersheds contribute less to the net benefits from regulations. Hence, to justify their control, the transaction costs associated with regulation of an additional watershed should be relatively small. For example, for *ex ante* quantity control, these costs should not exceed approximately \$600 thousands. This estimate is found by subtracting expected net benefits for 3 watersheds from expected net benefits for 8 watersheds, and dividing this difference by the difference in the number of watersheds controlled (five):

(\$12.3 million – \$9.6 million) / 5 watersheds $\approx$ \$600 thousands per watershed

If the transaction costs of regulating an extra watershed are high (around \$3 millions), the control of only the most polluting watershed is justified.

Comparison of efficiencies of the tax and quantity policies shows that the relative ranking of the policy instruments is independent from the policy spatial scopes. The tax mechanism performs better or at least as good as the quantity controls for all information scenarios and policy spatial scopes.

The policy scope above is selected based on the loadings to the mouth of a watershed. An alternative criterion can be the estimate of the loading to the Chesapeake Bay, the primary area of the policy concern. For example, let me consider the quantity controls. For the watershed 207 (the second most polluting), the nitrogen load to the mouth of the watershed is 5,456 ton (see Table 5.6). Although the watershed 202 is less polluting (3,667 ton), it contributes slightly more to the expected net benefits (8.3% versus 8.0%). The result is the same for the tax control (see Table 5.7). These outcomes can be explained by the difference in the shares of watersheds' loads transported to the Chesapeake Bay. On average 71% of the load from the watershed 202 reaches the Bay, while for the watershed 207 this share is only 58% (compare the mean transport coefficients for the watersheds in tables 5.6and 5.7). Hence, the loadings to the Bay can be better correlated with the benefits from watershed regulation.

Unfortunately, both the loadings to the mouth of a watershed and to the Chesapeake Bay are not easily observable, which complicates their use in the policy design.

Table 5.6. Improvement in Expected Net Benefits from Quantity Regulation of an Extra Watershed (as Percent From No Regulation Case)

watersheds	**Information scenarios**					**Average total load (ton)**	**Pollution transport coefficient**	
	Ex ante, %	***Pollution transport, %***	***Abatement cost, %***	***Damage cost, %***	***Ex post, %***		***mean***	***variance***
the rest	8.6	7.6	7.8	7.7	7.2	10,979	from 0.560 to 0.660	from 0.068 to 0.137
#202	8.3	7.4	7.8	8.4	8.5	3,667	0.710	0.110
#207	8.0	7.2	7.9	10.8	11.3	5,456	0.581	0.160
#204	13.5	14.0	16.3	29.4	32.3	8,926	0.731	0.114

Table 5.7. Improvement in Expected Net Benefits from Tax Regulation of an Extra Watershed (as Percent from No Regulation Case)

watersheds	**Information Scenarios**					**Average total load (ton)**	**Pollution transport coefficient**	
	Ex ante, %	***Pollution transport, %***	***Abatement cost, %***	***Damage cost, %***	***Ex post, %***		***mean***	***variance***
the rest	7.5	7.1	7.8	11.6	7.2	10,979	from 0.560 to 0.660	from 0.068 to 0.137
#202	7.6	8.1	7.8	13.7	8.5	3,667	0.710	0.110
#207	8.0	8.0	7.9	8.1	11.3	5,456	0.581	0.160
#204	17.0	17.6	16.3	26.7	32.3	8,926	0.731	0.114

5.4. Regulation of the most polluting watershed

If the transaction costs of a policy monitoring and enforcement are high, regulating just the most polluting watershed is justified. The analysis of the expected net benefits and information value for regulation of the watershed 202 (the watershed with the highest in the SRB loading to the mouth) are summarized in the Tables 5.8 – 5.10.

Table 5.8. Expected Net Benefits for the Quantity Controls of the Most Polluting Watershed, million dollars

Policy instruments	Information scenarios				
	Ex ante	***Pollution transport***	***Abatement costs***	***Damage costs***	***Ex post***
Input quantity controls	4.3	4.5	5.2	9.4	10.3
95% confidence interval		4.4-4.6	4.7-5.7	7.4-11.5	9.2-11.5
Input price controls	5.5	5.6	5.2	8.6	10.3
95% confidence interval		5.6-5.7	4.7-5.7	6.3-10.9	9.2-11.5
Difference between tax and quantity controls	1.1	1.1	0	Not statistically significant	0

Table 5.8 presents the expected net benefits for the alternative policy instruments and information scenarios. The difference between the ENB of tax and quantity mechanisms is small in absolute terms (compare last rows of the tables 5.8 and 5.1). However, this difference is significant if measured in terms of percent improvement from the no-regulation case. For the entire SRB region, the switch from quantity to tax control result in approximately 12% improvement in the expected net benefits, while for the regulation of one watershed the difference increases to approximately 25%.

VOI is presented in tables 5.9 and 5.10. Table 5.9 summarizes the results in absolute terms, and the next table describes the value of information in percent from the *ex ante* expected net benefits of the respective instruments. The relative value of different information types is the same for the regulations of one-watershed and the entire

SRB region (compare tables 5.1 and 5.8). However, in general, the information collection is more important for the one-watershed regulation. For one-watershed policy, perfect information collection is expected to improve the policy performance by up to 140% from the *ex ante* value, while for the whole region information collection is expected to increase ENB by 63% maximally.

Table 5.9. Value of Information for the Regulation of One Watershed, Million Dollars

	Information scenario			
	Pollution transport	***Abatement cost***	***Damage costs***	***Ex post***
Input quantity controls	0.2	0.9	5.1	6.0
Input taxes	0.1	close to zero	3.1	4.9
Difference	0.1	0.9	2.0	1.1

Table 5.10. Value of Information for the Mechanisms Targeted on the Most Polluting Watershed, as a *Percent* from of *Ex Ante* Expected Net Benefits

	Information scenario			
	Pollution transport	***Abatement costs***	***Damage costs***	***Ex post***
Input quantity controls	4.2	20.6	118.1	139.4
Input taxes	3.5	close to zero	57.1	89.7

5.5. Spatial Differentiation

To decrease the costs required for developing unique policies and monitoring schemes for each SRB watershed, a *uniform* policy can be applied, which prescribes the same level of regulation (i.e., land and fertilizer taxes/quotas) for all SRB watersheds. However, if the watersheds are highly heterogeneous in their abatement costs or pollution delivery characteristics, making the policy uniform significantly decreases the expected net benefits of the regulation. Hence, balancing the reductions in the transaction costs and expected net benefits is important for deciding the degree of the policy differentiation. The expected net benefits of uniform and differentiated tax and quantity controls in the SRB are compared in the tables 5.11 – 5.13.

Table 5.11 presents the expected net benefits of uniform tax and quantity controls for alternative information scenarios. The relative policy instrument ranking is not influenced by the degree of policy spatial differentiation. For differentiated (table 5.1) and uniform (table 5.11) policies, tax control performs better or at least no worse than the quantity control. The difference between the expected net benefits of the policies is similar for both uniform and differentiated policies.

Table 5.11. Expected Net Benefits for Uniform Tax and Quantity Controls, Million Dollars

	Information Scenarios				
	Ex ante	***Pollution transport***	***Abatement cost***	***Damage costs***	***Ex post***
Quantity, Uniform	12.1	12.2	13.5	19.0	20.0
95% confidence interval		12.1 -12.3	13.0-14.0	18.3-19.6	19.3-20.7
Tax, Uniform	13.6	13.7	13.5	19.3	20.0
95% confidence interval		13.6-13.8	13.0-14.0	18.7-19.9	19.3-20.7
Difference	1.5	1.5	0	Not statistically significant	0

Overall, the change in policy spatial differentiation has minor effect on policy performance. The difference in expected net benefits for the *ex ante* uniform and differentiated policies is $0.2 million (see table 5.12 and 5.13). For pollution transport information scenario, the difference is slightly higher - $0.4 millions and by $0.3 millions for quantity and tax control respectively. For other information scenarios, differentiated control also outperforms the uniform policy; however, the difference is not statistically significant.

Table 5.12. Expected Net Benefits for Differentiated and Uniform Quantity Control, Million Dollars

	Information scenarios				
	Ex ante	***Pollution transport***	***Abatement cost***	***Damage costs***	***Ex post***
Differentiated	12.3	12.6	13.7	19.2	20.1
95% confidence interval		12.5-12.6	13.2-14.2	18.6-19.7	19.4-20.8
Uniform	12.1	12.2	13.5	19.0	20.0
95% confidence interval		12.1 -12.3	13.0-14.0	18.3-19.6	19.3-20.7
Difference	0.2	0.4	Not statistically significant	Not statistically significant	Not statistically significant

The relatively small difference in expected net benefits for uniform and differentiated policies can be partially explained by the low degree of heterogeneity among watersheds captured in the model. Only two environmental impact parameters are different among the watersheds: loadings to the mouth of each watershed and pollution transport coefficients. In turn, the heterogeneity in abatement cost parameters is captured only by different baseline levels of land and fertilizer uses and the land prices. In reality, the SRB watersheds are more heterogeneous in both the economic and pollution transport characteristics. For example, the elasticities of agricultural land and fertilizer demand and supply can vary among watersheds. In response to environmental policy, the farmers in some watersheds can choose to alter their crop rotations. In other watersheds, the price of nitrogen fertilizer can change, causing further changes in corn production. Unfortunately, there were no data found that would allow modeling the whole range of differences in abatement costs and environmental impact types among the watersheds. As a result, the watershed heterogeneity is smaller in the model than it is in the real life. This simplification influences the relative performances of uniform versus differentiated policies and makes it smaller than it is in reality.

Table 5.13. Expected Net Benefits for Differentiated and Uniform Tax Control, Million Dollars

	Information scenarios				
	Ex ante	***Pollution transport***	***Abatement cost***	***Damage costs***	***Ex post***
Differentiated	13.8	14.0	13.7	19.3	20.1
95% confidence interval		14.0-14.1	13.2-14.2	18.7-19.9	19.4-20.8
Uniform	13.6	13.7	13.5	19.3	20.0
95% confidence interval		13.6-13.8	13.0-14.0	18.7-19.9	19.3-20.7
Difference	0.2	0.3	Not statistically significant	Not statistically significant	Not statistically significant

The value of information is not significantly affected by the degree of the policy differentiation (compare tables 5.2 and 5.3 with tables 5.14 and 5.15). The value of pollution transport information is slightly smaller for the uniform policy than for the differentiated one, while the value of the damage cost information is somewhat higher. The smaller value of the pollution transport information is due to the fact that the information about environmental impacts is underutilized for the uniform policies. The uniform policy prescribes the same taxes / aggregate quotas for all watersheds. Hence, the data about the watersheds' pollution transport parameters can be used to alter the overall level of the policy, but *not* to adjust the policy levels according to the unique characteristics of a watershed. Quite the opposite, for the differentiated policies, the data can be used to adjust both the overall policy level, and the regulation of each particular watershed. As a result, the value of pollution transport information is higher for the differentiated regulation.

Table 5.14. Expected Value of Information for Differentiated and Uniform Quantity Control, Million Dollars

	Information scenarios			
	Pollution transport	***Abatement cost***	***Damage costs***	***Ex post***
Quantity, Differentiated	0.3	1.4	6.9	7.8
Quantity, Uniform	0.1	1.4	6.9	7.9

Table 5.15. Expected Value of Information for Differentiated and Uniform Tax Control, Million Dollars

	Information scenarios			
	Pollution transport	Abatement cost	Damage	Ex post
Tax, Differentiated	0.2	close to zero	5.2	6.3
Tax, Uniform	0.1	close to zero	5.7	6.4

5.6. Alternative functional forms of the agricultural profits

The true functional form of the corn profits is not perfectly known. The decision makers can try to approximate the function or to assume a particular functional form based on their prior knowledge. In both cases, expected net benefits and information values are contingent on the functional form selected, and the effect of the assumption on policy decisions can be substantial. In my model, I compare the expected net benefits and value of information for quadratic expansion and CES profit functions. The analysis is performed only for the land and fertilizer *quantity* controls, because modeling tax controls for CES production is a very computationally intensive task. Tax control requires incorporation of possible polluters' responses to the policy. In the model, these polluters' responses are represented as constraints to the regulators' policy decision problem. The number of possible responses is proportional to the number of possible values of uncertain parameters. That is, for the sample size M = 1500, there are 1500 constraints in the model, and each constraint is nonlinear. There is no software available that can easily optimize an objective function subject to this number of nonlinear constraints.

The expected net benefits for the quantity policy are significantly altered by the assumption about the corn profit function. However, this effect depends on the information scenario considered. For the *ex ante* scenario, the difference in expected net benefits is 5.2 millions (i.e., approximately 40%, see table 5.16). The difference decreases, but is still significant for the pollution transport and abatement costs information scenarios. Finally, for the damage costs and the *ex post* information scenarios, the difference is 13% and 10% respectively. For these information scenarios, both functional forms give a wide range of results depending on the value of uncertain parameters considered. As a result, the 95% confidence interval for ENB is wide and the difference between policies is not statistically significant.

Table 5.16. Expected Net Benefits for Quantity Control Given Different Assumptions about the Functional Form of the Agricultural Profit, million dollars

	Information scenarios				
	Ex ante	***Pollution Transport***	***Abatement costs***	***Damage costs***	***Ex post***
Quadratic expansion	12.3	12.6	13.7	19.2	20.1
95% confidence interval		12.5-12.6	13.2-14.2	18.6-19.7	19.4-20.8
CES	17.5	17.6	17.9	21.7	22.0
95% confidence interval		17.5-17.6	17.4-18.5	19.0-24.4	19.2-24.7
Difference between CES and QE results	5.2	5.0	4.2	Not statistically significant	Not statistically significant

The relative value of different types of information is the same for both specifications of the agricultural profit function (compare tables 5.2 and 5.4 with 5.17 and 5.18). In both cases, the damage cost data are expected to have the highest value.

However, the value of information is approximately two times less for the CES specification of the production function. The difference in the information values can be explained by the relatively low sensitivity of the decisions based on CES versus quadratic expansion of the corn profits (see the deterministic analysis in the previous chapter)[10].

Table 5.17. Value of Information Given Alternative Specifications of the Agricultural Production Function, Million Dollars

	Information scenarios			
	Pollution transport	*Abatement costs*	*Damage costs*	*Ex post*
Quadratic expansion	0.3	1.4	6.9	7.8
CES	0.1	0.4	4.2	4.5

Significant difference in the expected net benefits and information values given the alternative specification of the social surplus function emphasizes the importance of the knowledge of the true functional form for making policy decisions.

Table 5.18. Value of Information Given Alternative Specifications of the Agricultural Production Function, Percent From *Ex Ante* Expected Net Benefits

	Information scenarios			
	Pollution transport	*Abatement cost*	*Damage costs*	*Ex post*
Quadratic expansion	2.0	11.2	55.7	63.7
CES	0.7	2.3	24.2	25.8

5.7. Alternative initial information about the pollution transport parameters

In assessing the probability distribution for the imperfectly known parameter, the goal is to incorporate whatever experience and evidence the decision makers have into a coherent distribution that best expresses their true beliefs and foreknowledge [Lawrence 1999]. Alternative distributions are possible given different initial knowledge or

[10] The low value of abatement cost information can not be explained by the deterministic analysis, because the DNB for the social surplus based on CES profits are sensitive to the abatement cost parameter values. Hence, further investigations are required to explain the result.

expertise of the decision makers. The assumption made about the distribution of imperfectly known parameters influences the estimates of policy expected net benefits and VOI. In the current research, the effects of the prior knowledge are illustrated for the example of the pollution transport coefficients. Two cases are considered: less informed decision maker with uniform believes about the transport coefficients, and a more informed decision maker with normal distribution for the coefficients.

The expected net benefits of regulation are lower for the less informed decision maker (see Table 5.19). The expected net benefits is approximately three times worse for the *ex ante*, pollution transport and abatement cost scenario. For the damage costs and *ex post* information scenarios, the difference in the expected net benefits is two-folds. These results are the same for both policy instruments.

Table 5.19. Expected Net Benefits Given Uniform Distribution of the Pollution Transport Coefficient, Million Dollars

	Information scenarios				
	Ex ante	***Pollution Transport***	***Abatement cost***	***Damage costs***	***Ex post***
Input quantity control	4.2	4.9	4.9	8.1	8.8
95% confidence interval		4.7-5.0	4.3-5.4	7.7-8.5	8.2-9.5
Input taxes	4.5	5.1	4.9	7.9	8.8
95% confidence interval		5.0-5.3	4.3-5.4	7.5-8.3	8.2-9.5
Difference	0.3	0.2	0	Not statistically significant	0

The prior knowledge of the decision maker about the transport parameters do not change the relative ranking of the policy instruments (compare tables 5.1 and 5.19): tax control performs better or at least no worse than the quantity control. However, the difference between policies is significantly smaller for the less informed decision maker.

In the model, the increased uncertainty about the pollution transport parameters is associated with the higher value of perfect information about these parameters (see Tables 5.20 – 5.23). Measured in absolute terms, the increase is approximately two-fold for both mechanisms. In percentage terms, the increase is even higher. For less informed decision maker, pollution transport information is expected to improve expected net benefits by 17% and 13% for quantity and tax mechanisms respectively, while for the more informed decision maker, this improvement is only 2% and 1.4%. For the decision maker who is less-informed, collecting the pollution transport information is the second priority after the damage cost data irregardless of policy instrument.

Table 5.20. Expected Value of Information for Land and Fertilizer Quantity Controls, Million Dollars

	Information scenarios			
	Pollution transport	***Abatement cost***	***Damage costs***	***Ex post***
Normal	0.3	1.4	6.9	7.8
Uniform	0.7	0.7	3.9	4.6

Table 5.21. Expected Value of Information for the Quantity Control as Percent from *Ex Ante* Expected Net Benefits

	Information scenarios			
	Pollution transport	***Abatement cost***	***Damage costs***	***Ex post***
Normal	2.0	11.2	55.7	63.7
Uniform	16.7	16.7	92.9	109.5

The value of abatement and damage costs information is smaller for less-informed decision-maker if measured in absolute terms (million dollars). However, the value of the data increases if measured in percent from the *ex ante* expected net benefits.

Table 5.22. Expected Value of Information for Tax Control, Million Dollars

	Information scenarios			
	Pollution Transport	Abatement costs	Damage costs	Ex post
Normal	0.2	close to zero	5.5	6.3
Uniform	0.6	close to zero	3.4	4.3

Table 5.23. Expected Value of Information for Tax Controls as Percent from the *Ex Ante* Expected Net Benefits

	Information scenarios			
	Pollution Transport	Abatement cost	Damage cost	Ex post
Normal	1.4	close to zero	39.9	45.7
Uniform	13.3	close to zero	75.6	95.6

Chapter 6. Conclusions

6.1. Overview

The latest *National Water Quality Inventory* indicates that nonpoint source (NPS) pollution is the leading contributor to water quality impairments. In particular, agricultural runoffs are responsible for 60 percent of the impaired river miles and half of the impaired lake acreage surveyed [US EPA 2003b]. One of the ways to solve the problem of NPS water pollution is to design and implement environmental policies that will induce agricultural producers to change their production practices and decrease environmental impacts [Ribaudo *et. al.* 1999]. An *efficient* environmental policy maximizes net economic benefits – the private net benefits of production (aggregate farm profits and benefits to owners of production inputs) minus the expected economic costs of pollution [Baumol and Oates 1988, Shortle and Horan 2001, Ribaudo *et. al.* 1999].

The information necessary to design economically efficient pollution control policies is almost always incomplete [NRC 2000, Ribaudo *et. al.* 1999]. The economic benefits from agricultural production are only privately known and uncertain from the regulators' perspectives (asymmetric information problem). The diffuse nature of pollution makes it extremely difficult (and costly) to monitor the runoffs and estimate the marginal environmental damages for individual polluters. In turn, the relationship between production practices and environmental damages are complex and poorly understood. Estimation of the damages requires knowledge of hydrologic processes driving the pollution fate and transport, biophysical relationships between pollution concentration and the states of water ecosystems, and economic factors affecting the economic demands for water system services [Ribaudo *et. al.* 1999]. The information about these relationships is usually unavailable. The uncertainties about economic benefits and environmental damages complicate designing an efficient environmental policy.

The determinants of the policy efficiency under uncertainty have been a subject of scientific research for approximately 30 years. Among the important factors, there are the choice of the indicator for monitoring polluters' compliances with the policy (e.g., polluting input use versus ambient concentrations), the policy mechanism used, the spatial allocation of pollution reductions, and the characteristics of uncertainty that the decision makers are facing. However, most of the theoretical studies focused on policy design under uncertainty are based on restrictive models. The assumptions about functional relationships and uncertainty characteristics made in analytical studies often make their conclusions too narrow to apply in a real-life situation. Several studies have investigated relative efficiency of policy instruments based on *empirical* modes (e.g., Carpentier *et. al.* 1998, Vatn *et. al.* 1997[11]). However, many of them assume deterministic situations with no uncertainty (e.g., Hopkins *et. al.* 1996, Weinberg and King 1996), or focus on one type of uncertainty, e.g., asymmetric information (e.g., Randhir and Lee 1997, Huang *et. al.* 1996).

In addition to selecting the policy designs, the decision makers can choose to invest into information collection to improve the performance of a selected policy. Given limited budgets and possibly high costs of data gathering, the priority directions for data collection should be identified. The choice of the priorities can be based on the expected increase in policy efficiency due to data collection, i.e. the value of information.

[11] For a comprehensive review see [Horan and Shortle 2001].

This study is focused on design of environmental policy to reduce nitrogen pollution from corn production in SRB and to estimate the value of information for the policies. *First*, the relative ranking of input price and quantity controls is examined. The regulations targets nitrogen fertilizer and land use, since these agricultural inputs directly affect the pollution runoffs and are relatively easy to monitor and control. Price control refers to taxes or subsidies, and quantity controls refer to aggregate trading quotas in each watershed. The *second* research question is the analysis of the value of alternative types of information for the alternative policy mechanisms. Three aggregate types of uncertainty are modeled: abatement cost, pollution fate and transport, and damage costs uncertainties. Accordingly, the efficiency of alternative policy instruments is estimated given five information scenarios: the baseline information (*ex ante*), or perfect information about the production profits/abatement costs; pollution transport, damage costs, or all the uncertain parameters. The value of information is the difference in the expected net benefits for the scenarios with improved and *ex ante* information.

The functional forms for environmental and economical processes affecting nitrogen pollution in SRB are not perfectly known. In addition, for each possible functional form, regulators can make different assumptions about possible parameter values. The policy efficiency and value of information results are conditional on the assumptions about functional form and parameters. Hence, the *third* research question is the study of the possible effects of these assumptions on the efficiency of input price and quantity controls in the SRB. Alternative (commonly used) functional forms of agricultural profits are analyzed; and different assumptions about the true values of transport coefficients and their probabilities are considered.

Finally, the efficiencies of the policy designs with smaller / higher information requirements are compared. Uniform policies (which impose uniform taxes or aggregate quotas in every SRB watershed) are compared with differentiated controls (which set unique requirements for each watershed based on estimated abatement costs and damages). Apart from this, the efficiencies of the policies for the entire region, or for one, two, or three watersheds with the highest nitrogen loads are compared.

Eight SRB watersheds are modeled. The benefits from corn production are simulated as a sum of corn producers' profits and economic surplus of the land suppliers. The model also simulates nitrogen runoff to the mouth of each watershed and pollution transport to the Chesapeake Bay. Environmental damage costs are modeled as an increasing convex function of the total loadings from the region to the Bay. To represent the uncertainties facing the decision maker, parameters in the functions representing economic benefits, pollution transport and damage costs, are modeled as random variables.

6.2. Research Results and Policy Implications

The following conclusions can be drawn from the analysis. First, in the region, land and fertilizer taxes perform better, or at least as good as, the aggregate trading quotas. However, the difference in the efficiency of the policy instruments depends on the information scenario considered: the less information is available, the more vital it is for the decision maker to select the policy instrument optimally. For example, for minimal information (*ex ante* information scenario), the difference between the instruments' efficiencies is \$1.5 million, while for the damage cost information scenario, the expected net benefits for the instruments are almost the same.

Collecting damage costs information has the highest priority for efficient policy design[12]. Improvement of the damage cost information results in 56% and 40% increase in efficiencies of the quantity and price controls respectively. For abatement cost and pollution transport information, the increase in policy efficiency is much smaller.

The value of all information types is higher for the quantity control than for the price regulation. The difference in the information value between price and quantity control ranges from $0.1 to $1.5 million for alternative information scenarios.

Given that the costs of information about individual watersheds are high, it can be justified to limit the regulation to one, two or three watersheds with the highest loadings. Regulating one watershed with the highest loading accounts for 40% and managing three the most polluting watersheds attributes for 80% of the expected net benefits form the pollution control in the entire region. Regulating five other watersheds increases policy efficiency by only 20%. Given high information costs, this contribution can be too low to justify the regulation of these low-polluting watersheds.

The degree of policy spatial differentiation does not significantly alter the relative policy efficiency. One of the reasons is the simplifications made in the model, particularly, the reduction of the heterogeneity among the watersheds in comparison with the real world.

The following factors influence *efficiency of a policy* under uncertainty:

1) Information structure. In line with Weitzman's result [1974], with the abatement cost information, policy mechanisms perform the same. For damage costs information scenario, efficiency of the input-based price and quantity policies is also similar. However, given ex ante or pollution transport information, the difference in the

[12] Note, that the costs of information gathering are not considered in the research

price and quantity instrument performances are high with the former instrument outperforming the later one.

2) Policy spatial differentiation and the degree of abatement and damage costs heterogeneity among watersheds. Efficiency of both policy instruments is lower for the uniform policy than for the differentiated one. However, the difference is small. Given possibly high costs of data collection, designing a unique policy for each watershed is not justified. However, this conclusion can be biased due to low degree of heterogeneity captured in the model. For example, the difference between the efficiencies of uniform and differentiated policies increases when watersheds' environmental impacts become potentially more different (e.g., when the transport coefficients are distributed uniformly with a larger variance allowed versus normal distributions assumed initially)

3) Functional relationships assumed for economic and biophysical processes in the region. For example, for the land and fertilizer quantity control, change in the assumption about the corn profit functional form causes $5.2 million difference in the estimate of ex ante policy efficiency.

The following determinants of the *value of information* are identified:

1) The policy mechanism selected. The value of information is higher for the input quantity control than for the input tax regulation.

2) Sensitivity of the policy decisions to changes in parameter values, and the amount of uncertainty about a parameter (measured by variance or entropy). For example, the value of the damage cost elasticity significantly affects the level of taxes and aggregate input use quotas chosen. The entropy (a measure of uncertainty) is also

high for the parameter. As a result, the value of the damage cost information (which includes data about the damage cost elasticity) has the highest value.

3) Prior knowledge of decision makers about the possible values of the uncertain parameters and their probabilities. The value of the pollution transport data for the tax policy is three times higher given the uniform probabilities of pollution transport coefficient values versus normal distribution.

4) The assumption about functional relationships in the system. The value of the abatement cost information for the land and fertilizer quantity control is 3.5 times higher when the quadratic approximation is used for agricultural profits instead of CES function.

6.3. Limitations and perspective for future studies

Current research is based on the model with corn production as the only agricultural sector (partial equilibrium analysis). This simplification restricts the flexibility of the farmers' responses to the regulation modeled. It does not allow simulation of the reallocation of agricultural lands between different agricultural practices as a result of the environmental control. This partial analysis influences the conclusions about policy expected net benefits and information values. For example, simulation of dairy and corn production simultaneously can increase the economic costs associated with environmental policy (i.e. decrease policy efficiency). Manure application is a main source of nitrogen in the corn production. Taxes or quantity limits on nitrogen fertilizer application would affect both corn and dairy profits, increasing the economic costs of environmental policy.

I do not account for point and urban source loadings. This simplification does not allow simulation of the redistribution of the pollution reductions among alternative source types. Such redistribution of load reductions decreases the environmental policy abatement costs, which is not captured in the model.

I also ignore the distortions of environmental policy results associated with other existing agricultural regulations (e.g., farm income policy). As noted by Shortle and Laughland [1994], Lewis [1996], and Peterson and Boisvert [2001], the implementation of environmental measures that increase production costs is not politically feasible unless accompanied by compensating adjustments in farm income support policies. Compensating the farms' losses due to environmental regulation often worsen policy environmental outcomes.

I also ignore the dynamic aspects of the production, pollution, and regulation process, such as the improvement in policy performance with time, modeling innovations, or analyzing the effect of the time of information collection on its value. As shown by Nordhause and Popp [1997], shift in the time of information acquisition can significantly alter the information value. For example, the information can have zero value if it reveals after the decision is made.

Finally, I do not model explicitly the information collection process; instead I compare the cases with ex ante or complete information about each of the imperfectly known parameter. However, it might be not optimal or feasible to collect complete information about any parameter. For example, Dinar and Xepapadeas [2002] consider a dynamic model that implies that perfect information can be achieved just with infinite investments. They show that steady state amount of information and investments in information collection depend on politically acceptable upper bound on environmental taxes. The lower the upper bound for the taxes, the larger knowledge accumulation / investments should be made. Lawrence [1999] presents a theoretical framework of analyzing optimal amount of information. He suggests that the data should be collected till the point where marginal benefits of information equal marginal costs. Note that in this analysis I leave out the whole issue of information collection costs.

The limitations described above are due to the following reasons: 1) the objective to make the research results general and relatively easy to interpret; 2) the lack of specific data; 3) computational difficulties that arise with complex nonlinear models.

There is a tradeoff between how realistic the model is and how simple it is and easy to interpret. Levins [1966] and Constanza *et. al.* [1990] described the fundamental trade-offs in modeling between realism, precision, and generality. No single model can maximize all three goals, and the choice of which objectives to pursue depends on fundamental purposes of the modeling study. My approach favors generality, and in striving for generality, the model gives up some realism and precision. Relationships are simplified and resolution is reduced.

Increased model complexity typically implies increased data requirements, which can lead to a feedback loop of increased complexity, requiring increasing data, etc [Bobba *et. al.* 2000]. The lack of the available data currently prevents from the construction of a more complex and realistic model. There is no study that would report the true form of the agricultural production functions in each of the sub-watersheds, or give the values of production function parameters, such as elasticities of input demand, supply or substitution. The same is true for the damage cost function. There is no study that would estimate in monetary terms the environmental effect of nitrogen pollution transported from SRB to the Chesapeake Bay, or report the functional form for the environmental damages.

Finally, the computation time for this model is large, and further complication of the model would require unreasonably long time to get the results with the available computation resources.

I consider this research as a useful starting point in empirical analysis of the link between information collection and environmental policy design, and much more researches on the topic should be done in future.

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Appendix A. Graphs and Data Tables

Figure A1. Structure of the Simulation Model

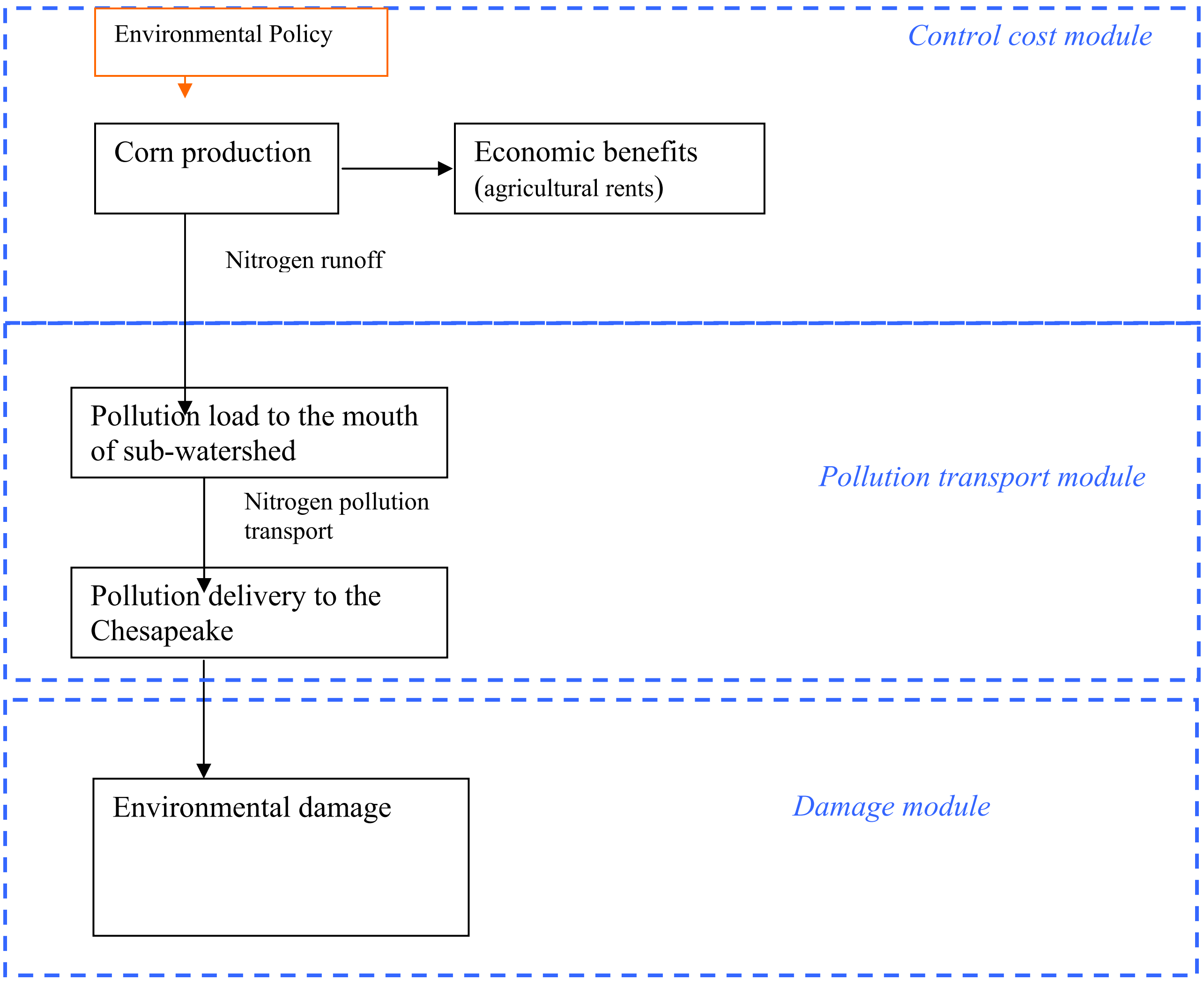

Figure A2. Watersheds in the Susquehanna River Basin in Pennsylvania [Horan et al 2002a]

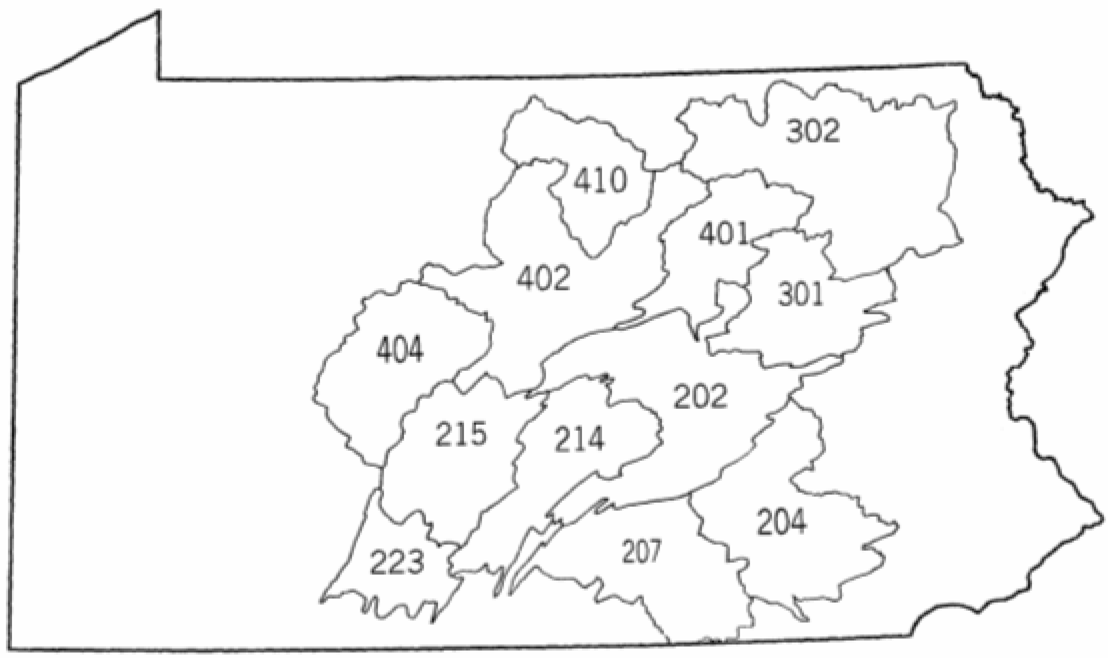

Table A1. Nitrogen pollution Load by Watershed

Watershed	Average NPS load (ton)	Average PS load (ton)	Average total load (ton)	Rank based on total load
202	3,500	167	3,667	3
204	5,694	3,231	8,926	1
207	4,314	1,142	5,456	2
214	1,499	72	1,571	7
215	1,981	77	2,057	6
223*	*1,492*	*29*	*1,521*	*8*
301	1,367	148	1,515	9
302	1,607	726	2,333	4
401	1,231	74	1,305	11
402	1,987	211	2,198	5
404*	*1,271*	*95*	*1,365*	*10*
410*	*459*	*68*	*527*	*12*

* watersheds in *italic* are dropped from the analysis
Source: ArcGWLF model output reported by Evans [2002-2003]

Table A2. Estimates of Damage Costs from Water Pollution

Damage Cost Estimates	Comments	Source
$2 to 8 billions annually	Annual costs of soil erosion	Ribaudo *et. al.* 1999
WTP for improvement of water to boatable conditions is $93; to fishable conditions - $70, to swimmable conditions - $78. Total household average WTP for improving national water quality to the standards set by Clean Water Act is $242.		Carson and Mitchell 1993
$1.8 - $8.7 billions with best guess of $4.6 billions (1978 dollars / year)	Total recreational damages from all forms of water pollution	Freeman 1982
$300 - $966 millions	recreational fishing benefits from controlling water pollution	Russell and Vaughan 1982
$9 billions per year	Annual damage due to runoff of agricultural chemicals to surface water only (lakes, rivers). National data	Ribaudo 1989
$D(t) = (180.75\ Z(t)^{0.352} – 146.63)\ h$ where h represents the number of households with water supply from the local groundwater, t is time of violation (from zero to 100, where t = 0 denotes current year).	Damage function for violation of groundwater nitrate standard (10 mg/l)	Poe 1998

Table A3. Baseline Corn and Agricultural Input Prices

	Price, $	Data Source
Corn, Metric Ton, p_y	76.8	Average value for 1996 – 2000; PA Agricultural Statistics [2003]
Nitrogen Fertilizer, Metric Ton, ρ	485.0	I assume that all fertilizer costs are attributed to nitrogen; PA Corn Budget [PSU 2000]
Land, Ha, r	161.6	ERS Cost and Return Survey [2003]
Composite mechanical input, w_M	1.0	The units of measurements of the input are selected to have the price of each unit equal one

Table A4. Baseline Data for Each Watershed

Watershed/ Characteristics	202	204	207	214	215	302	301 and 401	402
y_0 (10^3 ton)	602.1	1940.4	790.9	389.5	512.3	411.3	292.0	246.8
M_0 (10^3 units, price of each unit is one)	31891.9	102784.3	41892.9	20632.5	27138.1	21787.9	15469.8	13075.6
n_0, ton	11521.7	37133.2	15134.8	7454.0	9804.3	7871.4	5588.8	4723.9
l_0, ha	54085.7	174312.3	71046.3	34990.8	46023.6	36950.1	26235.3	22175.0
Intercept in the quadratic agricultural profit π_0 (10^6)	14.3	46.2	18.8	9.3	12.2	9.8	7.0	5.9
Load regression coefficient φ_1 (10^{-5})	646.0	486.9	205.2	552.2	386.5	646.0	92.4	429.5
Load regression coefficient φ_2 (10^{-12})	86017.5	8208.6	9212.0	54649.3	7425.0	86017.5	548.9	6905.0
Load regression coefficient φ_3 (10^2)	13620.6	52305.1	17480.5	9221.0	11067.8	13620.6	4642.4	12174.3
Calibration coefficient A (10^{-8})	3.3	9.1	26.1	1.3	8.6	2.3	326.9	42.4
Calibration coefficient μ	89542.7	101832.2	89663.2	115304.7	115304.7	88896.5	88896.5	88907.4
Precipitation (z_i), mm	817.5	929.7	818.6	1052.7	1052.7	811.6	811.6	811.7
NPS load, MT	3499.8	5694.2	4314.1	1499.2	1980.6	1607.0	2597.8	1987.1

Table A5. Expenditures in Corn Production ($/ton)*

Item	1996	1997	1998	1999	2000**	5-years average
Biological Input						
Fertilizers						
Fertilizer, lime and gypsum	15.6	13.1	11.3	10.9	10.7	12.3
soil conditioners	0.2	0.1	0.1	0.2	0.1	0.2
Manure	0.8	0.6	0.6	0.6	0.5	0.6
Total Fertilizers	16.6	13.9	12.0	11.6	11.4	13.1
Land	21.7	20.6	20.4	20.8	20.7	20.8
Total Biological Input	38.3	34.5	32.4	32.4	32.0	33.9
Share Of Land In Biological Input (b_1)	*0.6*	*0.6*	*0.6*	*0.6*	*0.6*	*0.6*
Share Of Biological Input In Total Expenditures (a_1)	*0.3*	*0.3*	*0.3*	*0.3*	*0.3*	*0.3*
Mechanical Input						
Labor						
Hired	1.4	1.4	1.3	1.4	1.5	1.4
Unpaid	12.9	11.9	11.6	12.0	12.2	12.1
Total Labor	14.4	13.2	12.9	13.5	13.7	13.5
Capital						
seed	9.5	9.1	8.8	9.1	9.0	9.1
capital recovery of machinery and equipment	23.3	21.5	21.8	22.2	22.6	22.3
taxes and insurance	2.4	2.1	2.0	2.0	2.0	2.1
repair	5.6	5.1	5.2	5.3	5.4	5.3
custom operations	3.5	3.3	3.1	3.2	3.0	3.2
interest	1.3	1.2	1.0	1.0	1.3	1.2
general farm overhead	4.8	5.0	4.5	4.3	4.3	4.6
Total Capital	50.5	47.5	46.5	47.1	47.6	47.8
Chemicals						
Chemicals	9.9	8.6	8.2	8.6	8.6	8.8
fuel, lube electricity	7.8	7.2	6.3	6.6	8.3	7.2
Total chemicals	17.8	15.9	14.5	15.2	16.8	16.0
Total Mechanical	82.6	76.5	73.9	75.8	78.1	77.4
Share of Mechanical Input in Total Costs ($1 - a_1$)	0.7	0.7	0.7	0.7	0.7	0.7
Total Costs	120.9	111.0	106.4	108.1	110.2	111.3

* The data in the USDA report are presented per planted acre. In our model, per bushel expenditures are necessary, so the USDA data were modified given per acre yield.

** The data for 2000 are preliminary.

Source: USDA Costs and Returns Survey [USDA 2001]

Table A6. Nitrogen and Land Demand Elasticities Reported by Different Studies.

Region	Nitrogen, own price	Land, own price	Nitrogen, cross-price	Source
Illinois, Indiana, and Ohio	-0.22		0.432	Hertel *et. al.* 1996
USA	Short-run, static: -0.54 Short-run, dynamic: -0.32 to –0.41 Long-run: -0.57 to –1.08			Abebe 1989
USA (crops)	-1.148			Roberts and Heady 1982
USA	-0.9			Gunjal *et. al.* 1980
USA	Short-run: - 0.23; Long-run: - 0.48		Short-run: 0.9; Long-run: 1.83	Denbaly 1991
North-East USA	-0.6 -0.449		0.018 -1.691	Heady and Yeh 1959
USA	Nonrandom static model: -0.693 Nonrandom dynamic model: -0.22 Random model, short run: -0.231 Random model, long-run: -0.591			Russell and Moriak 1970
Illinois **Indiana** **Iowa** **Missouri** **Ohio**	-0.121 -0.386 -0.409 -0.871 0.616	-0.024 -0.011 -0.023 -0.006 -0.007	-0.005 -0.006 -0.003 -0.003 -0.015	Vroomen and Larson 1991

Table A7. Characteristics of Random Parameters

Variable	Notation	Distribution	Characteristics
Own price elasticity of nitrogen demand	ε_N	Uniform	Mean = -0.5 Variance = 0.05 SD = 0.23 Coeff. of Var. = -0.46 Interval = [-0.9,-0.1] Entropy = -0.22
Own price elasticity of land demand	ε_L	Uniform	Mean = -0.32 Variance = 0.01 SD = 0.10 Coeff. of Var. = -0.33 Interval = [-0.5,-0.14] Entropy = -1.02
Cross-price elasticity of nitrogen demand	ε_{NL}	Uniform	Mean =0.40 Variance = 0.05 SD = 0.22 Coeff. of Var. = 0.55 Interval = [0.02, 0.8] Entropy = -0.27
Land and fertilizer substitution elasticity	σ_B	Uniform	Mean = 0.7 Variance = 0.1 SD = 0.3 Coeff. of Var. = 0.4 Interval = [0.2, 1.2] Entropy = 0.076
Substitution elasticity between composite mechanical and biological inputs	σ_α	Uniform	Mean = 0.5 Variance = 0.05 SD = 0.23 Coeff. of Var. = 0.46 Interval = [0.1, 0.9] Entropy = -0.22
Price elasticity of land supply	ε_{LS}	Uniform	Mean = 0.5 Variance = 0.08 SD = 0.28 Coeff. of Var. = 0.57 Interval = [0.01,0.99] Entropy = -0.02
Damage exponent	τ	Uniform	Mean = 2 Variance = 0.33 SD = 0.58 Coeff. of Var. = 0.29 Interval = [1, 3] Entropy = 0.69
Damage Coefficient	ψ	Uniform	Mean = $1.2\ 10^{-4}$ Variance = $2.1\ 10^{-9}$ SD = $4.6\ 10^{-5}$ Coeff. of Var. = 0.38 Interval = [$4\ 10^{-5}$, $2\ 10^{-4}$] Entropy = -8.74

Transport coefficient for watershed 202	ω_1	Normal / Uniform	*For Normal Distribution*: Mean = 0.710 Variance = 0.110 SD = 0.332 Coeff. of Var. = 0.467 Entropy = -0.801 *For Uniform Distribution*: Mean = 0.5 Variance = 0.083 SD = 0.288 Coeff. of Var. = 0.576 Interval = [0.001, 0.999] Entropy = -0.002
Transport coefficient for watershed 204	ω_2	Normal / Uniform	*For Normal Distribution*: Mean = 0.730 Variance = 0.110 SD = 0.338 Coeff. of Var. = 0.462 Interval = [0, 1] Entropy = -0.775 *For Uniform Distribution*: Mean = 0.5 Variance = 0.083 SD = 0.288 Coeff. of Var. = 0.576 Interval = [0.001, 0.999] Entropy = -0.002
Transport coefficient for watershed 207	ω_3	Normal / Uniform	*For Normal Distribution*: Mean = 0.580 Variance = 0.160 SD = 0.400 Coeff. of Var. = 0.688 Entropy = -0.430 *For Uniform Distribution*: Mean = 0.5 Variance = 0.083 SD = 0.288 Coeff. of Var. = 0.576 Interval = [0.001, 0.999] Entropy = -0.002

Transport coefficient for watershed 214	ω_4	Normal / Uniform	*For Normal Distribution*: Mean = 0.680 Variance = 0.130 SD = 0.355 Coeff. of Var. = 0.519 Entropy = -0.670 *For Uniform Distribution*: Mean = 0.5 Variance = 0.083 SD = 0.288 Coeff. of Var. = 0.576 Interval = [0.001, 0.999] Entropy = -0.002
Transport coefficient for watershed 215	ω_5	Normal / Uniform	*For Normal Distribution*: Mean = 0.630 Variance = 0.070 SD = 0.261 Coeff. of Var. = 0.417 Entropy = -1.269 *For Uniform Distribution*: Mean = 0.5 Variance = 0.083 SD = 0.288 Coeff. of Var. = 0.576 Interval = [0.001, 0.999] Entropy = -0.002
Transport coefficient for watershed 302	ω_6	Normal / Uniform	*For Normal Distribution*: Mean = 0.610 Variance = 0.070 SD = 0.265 Coeff. of Var. = 0.433 Entropy = -1.240 *For Uniform Distribution*: Mean = 0.5 Variance = 0.083 SD = 0.288 Coeff. of Var. = 0.576 Interval = [0.001, 0.999] Entropy = -0.002

Transport coefficient for combined watershed 301 and 401	ω_7	Normal / Uniform	*For Normal Distribution*: Mean = 0.660 Variance = 0.070 SD = 0.265 Coeff. of Var. = 0.401 Entropy = -1.240 *For Uniform Distribution*: Mean = 0.5 Variance = 0.083 SD = 0.288 Coeff. of Var. = 0.576 Interval = [0.001, 0.999] Entropy = -0.002
Transport coefficient for watershed 402	ω_8	Normal / Uniform	*For Normal Distribution*: Mean = 0.560 Variance = 0.140 SD = 0.370 Coeff. of Var. = 0.661 Entropy = -0.572 *For Uniform Distribution*: Mean = 0.5 Variance = 0.083 SD = 0.288 Coeff. of Var. = 0.576 Interval = [0.001, 0.999] Entropy = -0.002

Table A8. Approximation of Ex Ante Policy Performance With Monte Carlo Procedure

Sample size	SS, Quantity, ex ante, 10^6	Difference (%)	SS, Price, ex ante, 10^6	Difference (%)
100	437.1		473.0	
200	426.4	2.4	461.5	2.4
400	446.9	4.8	466.1	1.0
800	434.5	2.8	450.6	3.3
1500	443.5	2.1	458.4	1.7
3000	447.9	1.0	454.9	0.8
5000	450.1	0.5	456.4	0.3

Appendix B. Elasticity of input demand for CES function

From cost-minimization problem (42), the expressions for input demand are

$n' =$

$$c^{\frac{1}{1-\xi}} \rho^{\frac{1}{-1+\xi}} b_1^{\frac{1}{1-\xi}} b_2^{\frac{1}{-1+\xi}} \left(a_1 \left(b_2 + c^{-\frac{\xi}{-1+\xi}} \rho^{\frac{\xi}{-1+\xi}} b_1^{\frac{1}{1-\xi}} b_2^{\frac{\xi}{-1+\xi}} \right)^{\alpha/\xi} + c^{\frac{\alpha}{1-\alpha}} a_1^{\frac{\alpha}{-1+\alpha}} a_2^{\frac{1}{1-\alpha}} b_2^{\frac{\alpha}{-1+\alpha}} \left(b_2 + c^{-\frac{\xi}{-1+\xi}} \rho^{\frac{\xi}{-1+\xi}} b_1^{\frac{1}{1-\xi}} b_2^{\frac{\xi}{-1+\xi}} \right)^{\frac{\alpha(\alpha-\xi)}{(-1+\alpha)\xi}} w(x)^{\frac{\alpha}{-1+\alpha}} \right.$$

$l' =$

$$\left(a_1 \left(b_2 + c^{-\frac{\xi}{-1+\xi}} \rho^{\frac{\xi}{-1+\xi}} b_1^{\frac{1}{1-\xi}} b_2^{\frac{\xi}{-1+\xi}} \right)^{\alpha/\xi} + c^{\frac{\alpha}{1-\alpha}} a_1^{\frac{\alpha}{-1+\alpha}} a_2^{\frac{1}{1-\alpha}} b_2^{\frac{\alpha}{-1+\alpha}} \left(b_2 + c^{-\frac{\xi}{-1+\xi}} \rho^{\frac{\xi}{-1+\xi}} b_1^{\frac{1}{1-\xi}} b_2^{\frac{\xi}{-1+\xi}} \right)^{\frac{\alpha(\alpha-\xi)}{(-1+\alpha)\xi}} w(x)^{\frac{\alpha}{-1+\alpha}} \right)^{-1/\alpha}$$

$M' =$

$$c^{\frac{1}{1-\alpha}} a_1^{\frac{1}{-1+\alpha}} a_2^{\frac{1}{1-\alpha}} b_2^{\frac{1}{-1+\alpha}} \left(b_2 + c^{-\frac{\xi}{-1+\xi}} \rho^{\frac{\xi}{-1+\xi}} b_1^{\frac{1}{1-\xi}} b_2^{\frac{\xi}{-1+\xi}} \right)^{\frac{\alpha-\xi}{-\xi+\alpha\xi}} w(x)^{\frac{1}{-1+\alpha}}$$

$$\left(a_1 \left(b_2 + c^{-\frac{\xi}{-1+\xi}} \rho^{\frac{\xi}{-1+\xi}} b_1^{\frac{1}{1-\xi}} b_2^{\frac{\xi}{-1+\xi}} \right)^{\alpha/\xi} + c^{\frac{\alpha}{1-\alpha}} a_1^{\frac{\alpha}{-1+\alpha}} a_2^{\frac{1}{1-\alpha}} b_2^{\frac{\alpha}{-1+\alpha}} \left(b_2 + c^{-\frac{\xi}{-1+\xi}} \rho^{\frac{\xi}{-1+\xi}} b_1^{\frac{1}{1-\xi}} b_2^{\frac{\xi}{-1+\xi}} \right)^{\frac{\alpha(\alpha-\xi)}{(-1+\alpha)\xi}} w(x)^{\frac{\alpha}{-1+\alpha}} \right)^{-1/\alpha}$$

Given the input demand equations and the definition (43), the one can express the input demand elasticities as functions of substitution and distribution parameters (ξ, α, a_1, a_2, b_1, and b_2), and factor prices (w_M, r, and ρ).

$$\Xi_0 =$$

$$\left((-1+\xi)\, a_2 b_1 + r^{\frac{\xi}{-1+\xi}} (-1+\alpha)\, \rho^{\frac{\xi}{1-\xi}}\, a_2\, b_1^{\frac{\xi}{-1+\xi}}\, b_2^{\frac{1}{1-\xi}} + \right.$$

$$\left. r^{\frac{\xi}{-1+\xi}} (-1+\alpha)\, \rho^{\frac{1}{-1+\alpha}+\frac{1}{1-\xi}}\, a_1^{\frac{1}{1-\alpha}}\, a_2^{\frac{\alpha}{-1+\alpha}}\, b_1^{\frac{1}{1-\alpha}+\frac{1}{-1+\xi}}\, b_2^{\frac{1}{1-\xi}} \left(b_1 + r^{\frac{\xi}{-1+\xi}} \rho^{\frac{\xi}{1-\xi}}\, b_1^{\frac{\xi}{-1+\xi}}\, b_2^{\frac{1}{1-\xi}}\right)^{\frac{\alpha(-1+\xi)}{(-1+\alpha)\xi}} w_M^{\frac{\alpha}{1-\alpha}}\right) \Big/$$

$$\left((-1+\alpha)(-1+\xi)\left(b_1 + r^{\frac{\xi}{-1+\xi}} \rho^{\frac{\xi}{1-\xi}}\, b_1^{\frac{\xi}{-1+\xi}}\, b_2^{\frac{1}{1-\xi}}\right)\left(a_2 + \rho^{\frac{\alpha}{-1+\alpha}}\, a_1^{\frac{1}{1-\alpha}}\, a_2^{\frac{\alpha}{-1+\alpha}}\, b_1^{\frac{\alpha}{1-\alpha}} \left(b_1 + r^{\frac{\xi}{-1+\xi}} \rho^{\frac{\xi}{1-\xi}}\, b_1^{\frac{\xi}{-1+\xi}}\, b_2^{\frac{1}{1-\xi}}\right)^{\frac{\alpha(-1+\xi)}{(-1+\alpha)\xi}} w_M^{\frac{\alpha}{1-\alpha}}\right)\right)$$

$$\Xi_1 =$$

$$\frac{r^{\frac{\xi}{-1+\xi}} \rho^{\frac{\xi}{1-\xi}}\, b_1^{\frac{\xi}{-1+\xi}}\, b_2^{\frac{1}{1-\xi}} \left(\frac{1}{1-\xi} + \frac{a_2}{(-1+\alpha)\left(a_2 + \rho^{\frac{\alpha}{-1+\alpha}}\, a_1^{\frac{1}{1-\alpha}}\, a_2^{\frac{\alpha}{-1+\alpha}}\, b_1^{\frac{\alpha}{1-\alpha}} \left(b_1 + r^{\frac{\xi}{-1+\xi}} \rho^{\frac{\xi}{1-\xi}}\, b_1^{\frac{\xi}{-1+\xi}}\, b_2^{\frac{1}{1-\xi}}\right)^{\frac{\alpha(-1+\xi)}{(-1+\alpha)\xi}} w_M^{\frac{\alpha}{1-\alpha}}\right)}\right)}{b_1 + r^{\frac{\xi}{-1+\xi}} \rho^{\frac{\xi}{1-\xi}}\, b_1^{\frac{\xi}{-1+\xi}}\, b_2^{\frac{1}{1-\xi}}}$$

$\Xi_{al} =$

$$\frac{(-1+\alpha)\, a_2 b_1 + c^{\frac{\zeta}{-1+\zeta}} (-1+\zeta)\, \rho^{\frac{\zeta}{1-\zeta}} a_2 b_1^{\frac{\zeta}{-1+\zeta}} b_2^{\frac{1}{1-\zeta}} + (-1+\alpha)\, \rho^{\frac{\alpha}{-1+\alpha}} a_1^{\frac{1}{1-\alpha}} a_2^{\frac{\alpha}{-1+\alpha}} b_1^{\frac{1}{1-\alpha}} \left(b_1 + c^{\frac{\zeta}{-1+\zeta}} \rho^{\frac{\zeta}{1-\zeta}} b_1^{\frac{\zeta}{-1+\zeta}} b_2^{\frac{1}{1-\zeta}}\right)^{\frac{\alpha(-1+\zeta)}{(-1+\alpha)\zeta}} w_{M0}^{\frac{\alpha}{1-\alpha}}}{(-1+\alpha)(-1+\zeta) \left(b_1 + c^{\frac{\zeta}{-1+\zeta}} \rho^{\frac{\zeta}{1-\zeta}} b_1^{\frac{\zeta}{-1+\zeta}} b_2^{\frac{1}{1-\zeta}}\right) \left(a_2 + \rho^{\frac{\alpha}{-1+\alpha}} a_1^{\frac{1}{1-\alpha}} a_2^{\frac{\alpha}{-1+\alpha}} b_1^{\frac{\alpha}{1-\alpha}} \left(b_1 + c^{\frac{\zeta}{-1+\zeta}} \rho^{\frac{\zeta}{1-\zeta}} b_1^{\frac{\zeta}{-1+\zeta}} b_2^{\frac{1}{1-\zeta}}\right)^{\frac{\alpha(-1+\zeta)}{(-1+\alpha)\zeta}} w_{M0}^{\frac{\alpha}{1-\alpha}}\right)}$$

The elasticity values are found given the baseline input prices $r = r_0$, $w_M = w_{M0}$, and $\rho = \rho_0$.

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A Generic Tool For Evaluating The Utility Of Selected Pollution Mitigation Strategies Within A Watershed PREDICT: User's Manual. (with B. Evans, D. Lehning, K. Corradini, and S. Sheeder). Envronmental Resources Research Institute, PSU. Summary is available at http://www.orser.psu.edu/gissupport/predict.pdf

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